Power Quality Disturbance Detection and Classification

Swastik Sovan Panda

Department of Electrical Engineering

National Institute of Technology Rourkela

Power Quality Disturbance Detection and Classification

Dissertation submitted in partial fulfillment

of the requirements of the degree of

Bachelor of Technology

in

Electrical Engineering

by

Swastik Sovan Panda

(Roll Number: 112EE0247)

based on research carried out

under the supervision of

Prof. Sanjeeb Mohanty

Department of Electrical Engineering

National Institute of Technology Rourkela

Department of Electrical Engineering
National Institute of Technology Rourkela

May 10,2016

Certificate of Examination

Roll Number: *112EE0247*

Name: *Swastik Sovan Panda*

Title of Dissertation: *Power Quality Disturbance Detection and Classification*

We the below signed, after checking the dissertation mentioned above and the official record book (s) of the student, hereby state our approval of the dissertation submitted in partial fulfillment of the requirements of the degree of *Bachelor of Technology* in *Electrical Engineering* at *National Institute of Technology Rourkela*. We are satisfied with the volume, quality, correctness, and originality of the work.

HOD	Principal Supervisor
Prof. J. K. Satpathy	**Prof. Sanjeeb Mohanty**

Department of Electrical Engineering
National Institute of Technology Rourkela

May 10, 2016

Supervisors’ Certificate

This is to certify that the work presented in the dissertation entitled *Power Quality Disturbance Detection and Classification* submitted by *Swastik Sovan Panda*, Roll Number 112EE0247 is a record of original research carried out by him under our supervision and guidance in partial fulfillment of the requirements of the degree of *Bachelor of Technology* in *Electrical Engineering*. Neither this dissertation nor any part of it has been submitted earlier for any degree or diploma to any institute or university in India or abroad.

HOD	Principal Supervisor
Prof. J. K. Satpathy	Prof. Sanjeeb Mohanty

Declaration of Originality

I, *Swastik Sovan Panda*, Roll Number *112EE0247* hereby declare that this dissertation entitled *Power Quality Disturbance Detection and Classification* presents my original work carried out as a bachelor student of NIT Rourkela and, to the best of my knowledge, contains no material previously published or written by another person, nor any material presented by me for the award of any degree or diploma of NIT Rourkela or any other institution. Any contribution made to this research by others, with whom I have worked at NIT Rourkela or elsewhere, is explicitly acknowledged in the dissertation. Works of other authors cited in this dissertation have been duly acknowledged under the sections "Reference" or "Bibliography". I have also submitted my original research records to the scrutiny committee for evaluation of my dissertation.

I am fully aware that in case of any non-compliance detected in future, the Senate of NIT Rourkela may withdraw the degree awarded to me on the basis of the present dissertation.

May, 10
NIT Rourkela

Swastik Sovan Panda

Acknowledgment

I would like to express my sincere gratitude to my supervisor **Prof. Sanjeeb Mohanty** for his guidance, encouragement, and support throughout the course of this work. It was an invaluable learning experience for me to be one of his students. As my supervisor his insight, observations and suggestions helped me to establish the overall direction of the research and contributed immensely for the success of this work.

I express my gratitude to **Prof. J. K. Satpathy,** Head of the Department, Electrical Engineering for his invaluable suggestions and constant encouragement all through this work.

I would also like to acknowledge the entire teaching and non-teaching staff of Electrical department for establishing a working environment and for constructive discussions.

Finally, I am always indebted to all my family members, especially my parents, for their endless support and love.

May 10, 2016 *Swastik Sovan Panda*

NIT Rourkela Roll Number: 112EE0247

Abstract

Power quality (PQ) monitoring is an essential service that many utilities perform for their industrial and larger commercial customers. Detecting and classifying the different electrical disturbances which can cause PQ problems is a difficult task that requires a high level of engineering knowledge. The vast majority of the disturbances are non-stationary and transitory in nature subsequently it requires advanced instruments and procedures for the examination of PQ disturbances. In this work a hybrid procedure is utilized for describing PQ disturbances utilizing wavelet transform and fuzzy logic. A no of PQ occasions are produced and decomposed utilizing wavelet decomposition algorithm of wavelet transform for exact recognition of disturbances. It is likewise watched that when the PQ disturbances are contaminated with noise the identification gets to be troublesome and the feature vectors to be separated will contain a high amount of noise which may corrupt the characterization precision. Consequently a Wavelet based denoising system is proposed in this work before feature extraction process. Two extremely distinct features basic to all PQ disturbances like Energy and Total Harmonic Distortion (THD) are separated utilizing discrete wavelet transform and is nourished as inputs to the fuzzy expert system for precise recognition and order of different PQ disturbances. The fuzzy expert system classifies the PQ disturbances as well as demonstrates whether the disturbance is unadulterated or contains harmonics. A neural network based Power Quality Disturbance (PQD) recognition framework is additionally displayed executing Multilayer Feedforward Neural Network (MFNN).

Keywords: Power Quality; MFNN; Fuzzy Expert; Wavelet; Feature Extraction

Table of Contents

6. Classification Using Fuzzy Expert System

7. Conclusion and Future Scope of work

List of Figures

List of Tables

List of Abbreviations

ANN .... Artificial Neural Network

BPA .... Back Propagation Algorithm

CWT .... Continuous Wavelet Transform

DWT .... Discrete Wavelet Transform

FL .... Fuzzy Logic

FT .... Fourier Transform

MAE .... Mean Absolute Error

MFNN .... Multilayer Feedforward Neural Network

NN .... Neural Network

MSE .... Mean Square Error

PE .... Processing Elements

PQ .... Power Quality

PQD .... Power Quality Disturbance

RMS .... Root Mean Square

SNR .... Signal to Noise Ratio

STFT .... Short Time Fourier Transform

THD .... Total Harmonic Distortion

WT .... Wavelet Transform

Chapter 1

Introduction

The power quality examination is a critical component in the cutting edge power frameworks. The electrical engineer must comprehend a specific statistical information and framework when they break down the electric power quality issues. POWER QUALITY (PQ) is typically characterized as the investigation of the nature of electric power signals. Lately, grid users have distinguished an expanding number of downsides created by electric PQ variation. The hardware utilized with electrical utility are much more delicate to power quality (PQ) variation than before. The gear utilized are for the most part advanced or chip based containing power electronic segments which are sensitive to power quality disturbances. Subsequently, nowadays, clients request more elevated amounts of PQ to guarantee the best possible operation of such sensitive gear. The PQ of electrical power is normally ascribed to electrical cable aggravations, for example, waveshape issues, overvoltages, capacitor switching transients, harmonic distortion, and impulse transients. In this way, electromagnetic transients, which are fleeting voltage surges sufficiently capable to smash a generator shaft, can bring about sudden disastrous harm. Harmonics, infrequently alluded to as electrical contamination, are bends of the typical voltage waveforms found in AC transmission, which can emerge at for point in a power system. While harmonics can be as dangerous as transients, frequently the greatest harm from these mutilations lies in the loss of validity of the power utilities on the side of their customers. A large portion of the disturbances are non-stationary in nature henceforth it requires advanced techniques and systems for the examination of PQ disturbances. A typical Fourier transform is not a reasonable instrument for investigation of PQ aggravations as it gives just spectrum data of the signal without the time limitation data which is required to discover the begin time and end time and additionally the interim of the disturbance. The Short Time Fourier Transform (STFT) is another signal handling system but it is appropriate for stationary signs where the frequency does not change with time. However for non-stationary signs STFT does not perceive the signal dynamics because of the limitation of fixed window width. The time-frequency investigation procedure is more fitting for breaking down non-stationary signal since it gives both time and spectral data of the signal. The Discrete Wavelet Transform

(DWT) is favored on the grounds that it utilizes an adaptable window to recognize the time-frequency variations which results in a superior time-frequency resolution.

1.2 Literature Survey

Broad exploration works have been sought after in the region of utilization of advanced signal handling systems to power quality event analysis. Santoso et al.[6] utilized the Wavelet Transform (WT) along with the Fourier transform to extract unique features from the voltage and current waveforms that portray power quality events. The Fourier transform is used to portray steady state phenomena and the WT is applied to transient phenomena. Wright et al. [2] have connected Short time Fourier change (STFT) which is another signal processing method yet it is appropriate for stationary signal where the frequency does not vacillate with timeHowever for non-stationary signal STFT does not perceive the signal dynamics due to the restriction of fixed window width. The WT is an incredible tool for analyzing non-stationary signals and it vanquishes the disadvantage of STFT . It disintegrates the signal into time scale representation as opposed to time-frequency representation. The DWT is an incredible computing and mathematical tool which has been utilized as a part of connected arithmetic, signal preparing and others. In wavelet investigation, the utilization of a completely versatile regulated window can deal with the signal cutting issue. The fundamental thought of this technique is to see the signal at various resolution. Subsequently the WT has been investigated broadly in different studies as a differentiating choice to STFT [7-9]. Abdelazeem et al [7] displayed a cross breed procedure for identifying and depicting power quality disturbances utilizing WT, Kalman channel and fuzzy rationale. L.C Saikia et al [8] have contemplated a system considering the WT and the manufactured neural system for describing power quality disturbances. The Support Vector Machine (SVM) was presented in a few written works [10], [11] as an apparatus for classification. In the recent days wavelet change in conjunctions with artificial intelligence strategy is utilized prevalently to characterize power quality. A few written works are accounted for in [12-18] yet there exists a trouble in portraying i.e. the testing signal frequently have noise. Wei Bing Hu et al [20] have built up a method taking into account the wavelet change for de-noising of power quality occasion. To defeat the troubles of extraction of the component vector of the disturbance out of the noises in a low SNR atmosphere, a de-noising system is proposed. Chuah Heng Keow et al [21] have proposed a procedure for upgrading power quality issue arrangement in light of the wavelet change and a principle based technique.

1.3 Motivation and Objective of the Work

From the literature survey it can be easily understood that the discrete wavelet transformation (DWT) is a powerful figuring and scientific apparatus which has been utilized freely as a part of connected science, signal preparing and all the more critically in the zone of power quality analysis. The main cause behind the degradation of power quality is the power line disturbances. With an end goal to discover a solution for the above issue, one needs to recognize and order the power quality disturbances precisely for further examining and research. This gives ample motivation to work on the above area using the advanced signal processing techniques and artificial intelligence. The primary idea of this work is to look at the signal at different resolution. In this work, the produced signs are decomposed into various levels through wavelet transform and any adjustment in smoothness of the signal is distinguished. This work demonstrates that every power quality disturbance has one of a kind deviation from the unadulterated sinusoidal waveform and this is received to give a solid characterization of various sort of disturbance. The target of this work is:

- To simulate different power quality disturbances
- To detect the different disturbances by using wavelet transform
- To de-noise the disturbances polluted with noise
- To model a PQD system using neural network
- To classify PQ disturbances using fuzzy expert system

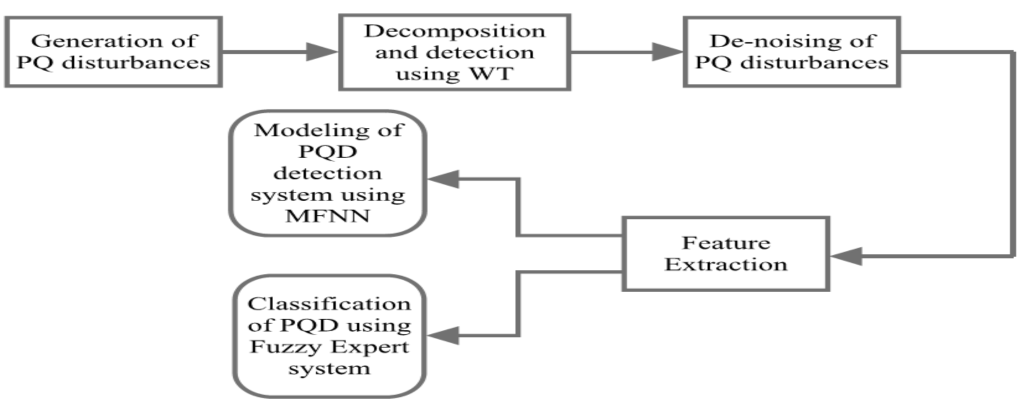

Figure 3.1 Block Diagram of the method adopted

1.4 Thesis Layout

Chapter 1 audits the writing on different power quality issues and portrayal of power quality disturbances. The Literatures are additionally checked on the wavelet transform as a method for investigating distinctive power quality occasions in conjunction with the computerized reasoning strategy. The inspiration and objective alongside brief depiction of the work is shown.

Chapter 2 portrays the instrument of wavelet transform and disintegration algorithm elaborately and distinctive PQ disturbances are reproduced and decomposed utilizing wavelet decomposition calculation and effective discovery of all disturbances is done. Different decomposition parameters like decision of mother wavelet and choice of most extreme decay levels are determined. The issues in regards to recognition in presence of noise are talked about.

Chapter 3 utilizes wavelet based de-noising strategy for extraction of noise free PQ disturbances. The different issues in regards to de-noising like determination of thresholding capacity and thresholding guidelines are talked about and different execution files for describing a compelling de-noising strategy are inspected and surveyed.

Chapter 4 manages the element extraction. In order to train the neural network for showing a power quality disturbance (PQD) location structure and commitment to the fuzzy expert framework, the Energy and THD are utilized as the element vector for setting up the input-output data of diverse PQ disturbances.

Chapter 5 utilizes a Multilayer Feedforward Neural Network (MFNN) for displaying a PQD recognition framework. Features extracted in part 4 are utilized as input-output information for training purposes and root mean square error and mean absolute error were gotten.

Chapter 6 utilizes a fuzzy expert framework for grouping particular PQ disturbances and classification accuracy of each PQ disturbance was discovered.

Chapter 7 abridges the outcomes acquired in every section and future extent of work is examined in a nutshell.

Chapter 2

Decomposition Using Wavelet Transform

2.1 Introduction

Nowadays with the invention of the digital techniques, the PQ disturbances are monitored onsite and online. The detection of PQ disturbances has undergone significant advancements after the use of wavelet transform(WT) recently. Whereas FT and STFT use exponential basis functions, the WT uses a wavelet basis function which gives much better results. The wavelet basis function scales itself in accordance with the frequency under examination. The signal is decomposed into several different frequency levels using wavelet transform and these are called as wavelet coefficients. There are two types of WT based on the type of signal: continuous wavelet transform (CWT) and discrete wavelet transform (DWT). DWT based decomposition is used for discrete time signal and CWT based decomposition is utilized for continuous time signal. As all signals in this work are discrete in nature, DWT is used predominantly. In this section different PQ disturbances like Sag, Swell, Interruption, Sag with harmonics and Swell with harmonics are simulated with the help of MATLAB. Further wavelet coefficients are found with the help of DWT and the type of disturbance is found and recognized.

2.2 Discrete Wavelet Transform (DWT)

In wavelet investigation, the Discrete Wavelet Transform (DWT) decays a sign into an arrangement of commonly orthogonal wavelet basis functions. These functions contrast from sinusoidal basic functions in that they are spatially limited – that is, nonzero over just part of the aggregate signal length. Moreover, wavelet capacities are expanded, deciphered and scaled forms of a typical function φ, known as the mother wavelet. The DWT is invertible, so that the original signal can be totally recouped from its DWT representation.

The DWT assessment has two stages. Determination of wavelet coefficients $h_d(n)$ and $g_d(n)$ is the principal stage. *X(n)* in the wavelet domain is represented by these coefficients. From these coefficients, calculation of both the approximated and detailed version of the original signal is achieved, these wavelet coefficients are called $cA_1(n)$ and $cD_1(n)$ as defined below:

$$cD_1(n) = \sum_{k=-\infty}^{\infty} X(k).\, g_d(2n-k) \tag{2.1}$$

$$cA_1(n) = \sum_{k=-\infty}^{\infty} X(k).\, h_d(2n-k) \tag{2.2}$$

The same process is applied to calculate the coefficients of all corresponding levels. While the low pass filter approximates the signal, the high pass filter gives the subtle elements lost in the estimate. The approximations are low-frequency high scale segment while the details are high-frequency low scale part. The wavelet transform (WT) of a signal *X(t)* is stated as:

$$WT_x(a,b) = \int_{-\infty}^{\infty} X(t)\psi^*_{a,b}\, dt \tag{2.3}$$

Where $\psi_{a,b}(t) = \frac{\psi\left(\frac{t-b}{a}\right)}{\sqrt{a}}$ (2.4)

is a scaled and shifted version of the mother wavelet Ψ(t).The parameter *a* corresponds to scale and frequency domain property of Ψ(t). The parameter *b* corresponds to time domain property of Ψ(t). In addition, $1/\sqrt{a}$ is the normalization value of $\psi_{a,b}(t)$ for having spectrum power as same as mother wavelet in every scale.

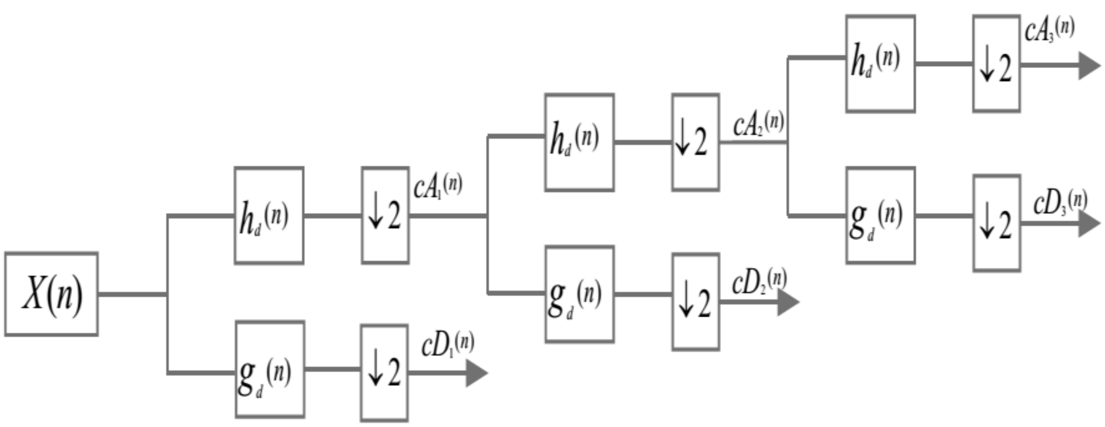

Figure 2.1 Decomposition Algorithm

Where

$h_d[n]$ = Impulse response of LPF

$g_d[n]$ = Impulse response of HPF

X(n) = Discretized original signal

cA1(n) =Approximate coefficient of level 1 decomposition/output of first LPF

cD1(n) = Detail coefficient of level 1 decomposition/output of first HPF

cA2 (n) =Approximate coefficient of level 2 decomposition/output of 2nd LPF

cD2(n) = Detail coefficient of level 2 decomposition/output of 2nd HPF

cA3 (n) =Approximate coefficient of level 3 decomposition/output of 3rd LPF

cD3(n) = Detail coefficient of level 3 decomposition/output of 3rd HPF

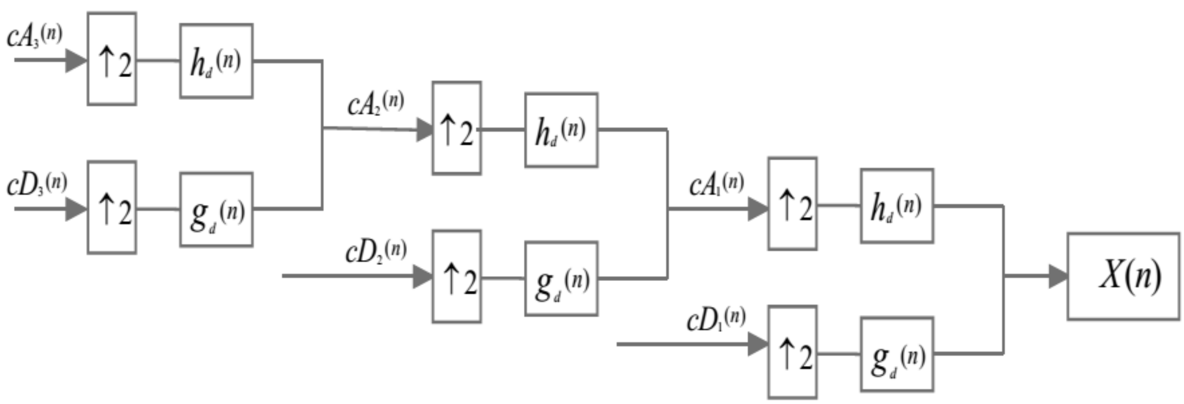

Figure 2.2 Reconstruction Algorithm

2.2.1 Choice of Mother Wavelet

The selection of mother wavelet is an essential issue for decomposition of PQ disturbances as the correct choice of mother wavelet results in precise detection of disturbances. There are several mother wavelets such as Daubechies, Morlet, Haar, Symlet etc. exists in wavelet library but literature survey showed that for power quality analysis Daubechies wavelet gives the desired result. The Daubechies wavelets with 4, 6, 8, and10 filter coefficients work well in most disturbance cases. In this work, daub 8 is predominantly used.

2.2.2 Selection of maximum decomposition level

In the DWT, *Jmax = fix(log2 n)* controls the most extreme decomposition level of a signal is where *n* is the length of the signal; fix adjusts the worth in the section to its closest number.

However in practice, for a wavelet based de-noising, maximum decomposition level is selected according to the ease and necessity.

2.3 Generation of PQ disturbances

The various power quality disturbances such as Sag, Swell, Interruption, and Sag with harmonics and Swell with harmonics are generated with different magnitudes using MATLAB.

2.3.1 Signal specification

T_s (time period) =0.5 sec

f_s (sampling frequency) =6.4 KHz

f=50Hz

No of cycles=25

No of samples/cycle=128

Total Sampling points=3200

Duration of disturbance=0.2 second. The interval of disturbance from 0.2 to 0.4 second of time which is between 1250 to 2500 sampling points.

2.3.2 Parametric model of PQ disturbances

Table 2.1 Equations and parameter variations for PQ signals

PQ Disturbance	Model	Parameter Variations
Voltage Sag	$X(t)=A(1-\alpha(u(t-t_1)$ $-u(t-t_2)))\sin(wt)$ $t_1<t_2$; $u(t)=1$ if $t \geq 0$, $u(t)=0$ if $t < 0$	$0.1 \leq \alpha \leq 0.9$ $T \leq t_2-t_1 \leq 10T$
Voltage Swell	$X(t)=A(1+\alpha(u(t-t_1)$ $-u(t-t_2)))\sin(wt)$ $t_1<t_2$; $u(t)=1$ if $t \geq 0$, $u(t)=0$ if $t < 0$	$0.1 \leq \alpha \leq 0.9$ $T \leq t_2-t_1 \leq 10T$

Interruption	$X(t)=A(1-\alpha(u(t-t_1)$ $-u(t-t_2)))\sin(wt)$	$0.01 \leq \alpha \leq 0.09$ $T \leq t_2-t_1 \leq 10T$
Voltage Sag With Harmonics	$X(t)=A(1-\alpha(u(t-t_1)$ $-u(t-t_2)))(\alpha_1\sin(wt)$ $\alpha_2\sin(2wt) + \alpha_3\sin(3wt)$ $+ \alpha_5\sin(5wt)+ \alpha_7\sin(7wt))$	$\alpha_1=1$ $0 \leq \alpha_2$, α_3 ,α_5 and $\alpha_7 \leq 0.3$ $0.1 \leq \alpha \leq 0.9$ $T \leq t_2-t_1 \leq 10T$
Voltage Swell With Harmonics	$X(t)=A(1+\alpha(u(t-t_1)$ $-u(t-t_2)))(\alpha_1\sin(wt)$ $\alpha_2\sin(2wt) + \alpha_3\sin(3wt)$ $+ \alpha_5\sin(5wt)+ \alpha_7\sin(7wt))$	$\alpha_1=1$ $0 \leq \alpha_2$, α_3 ,α_5 and $\alpha_7 \leq 0.3$ $0.1 \leq \alpha \leq 0.9$ $T \leq t_2-t_1 \leq 10T$

The parameter α means the level of sag or swell in the initial two types of disturbances. The unit step function u(t) in the table gives the time term of disturbances present in the immaculate sine waveform. Amid the procedure of generation of disturbance signal from the parametric model, the estimation of α and the position of u(t) has been fluctuated reasonably, so that countless signals can be generated by shifting size (by evolving α) on various focuses on the wave (by changing the parameters t1 and t2) and the span of the aggravation (t2-t1).

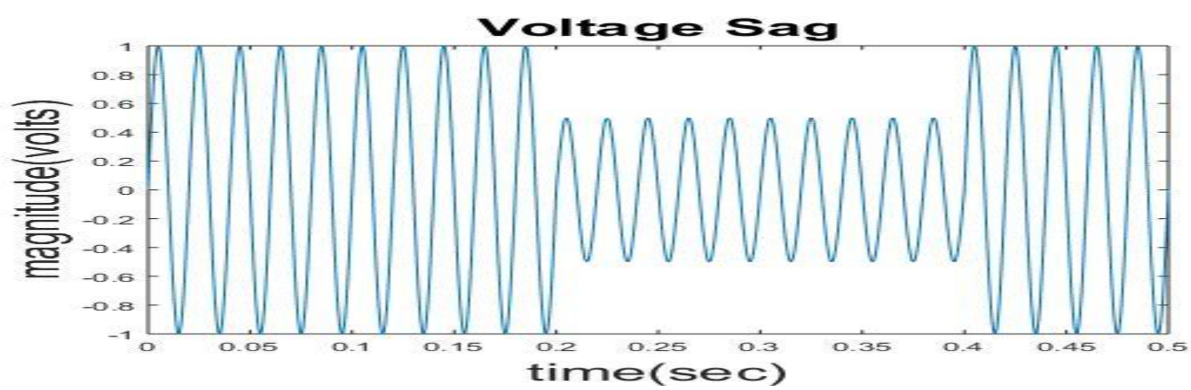

Figure 2.3 Voltage Sag

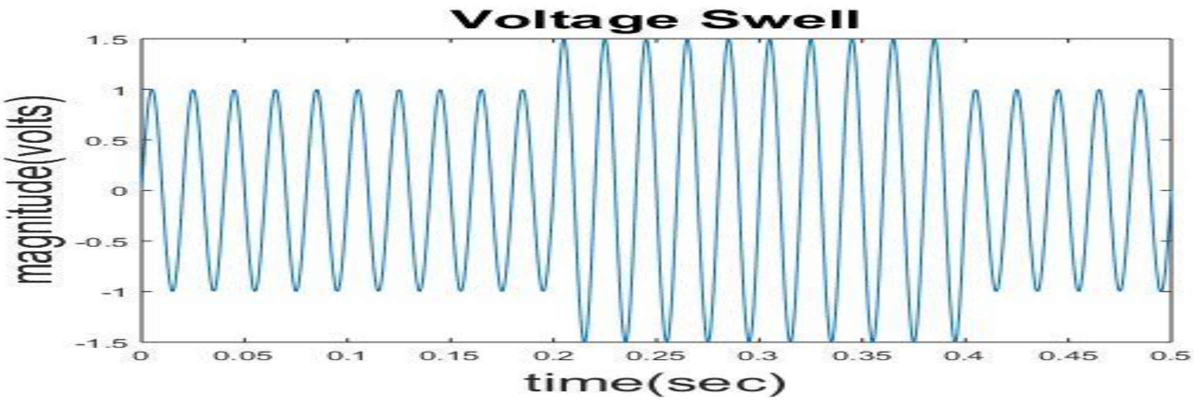

Figure 2.4 Voltage Swell

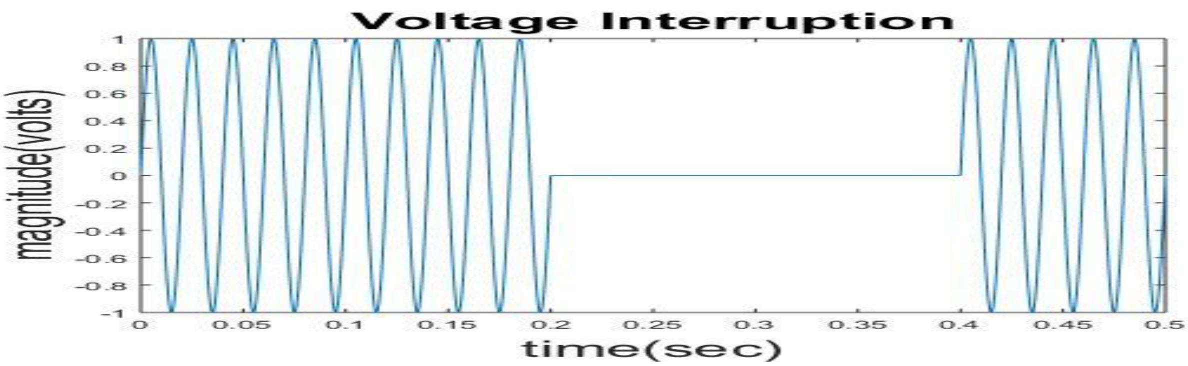

Figure 2.5 Voltage Interruption

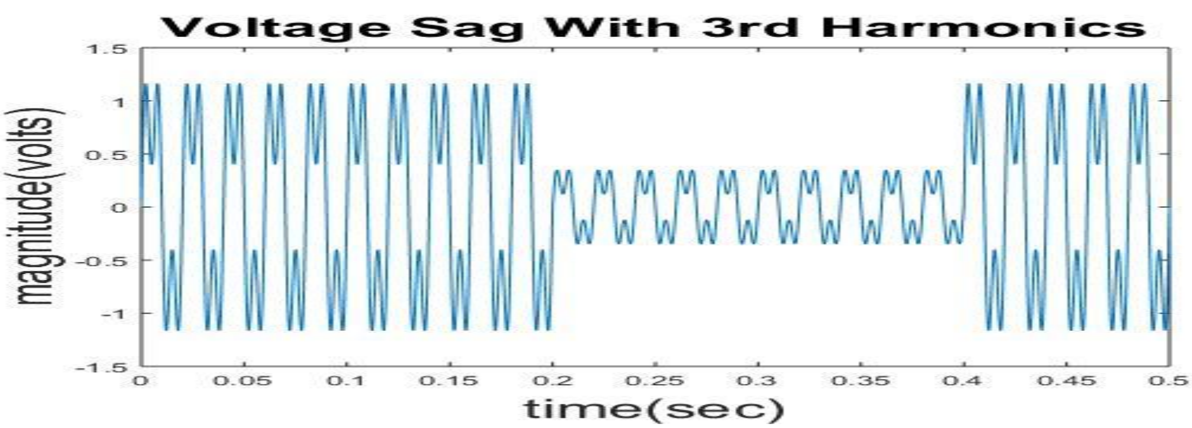

Figure 2.6 Voltage Sag With 3rd Harmonics

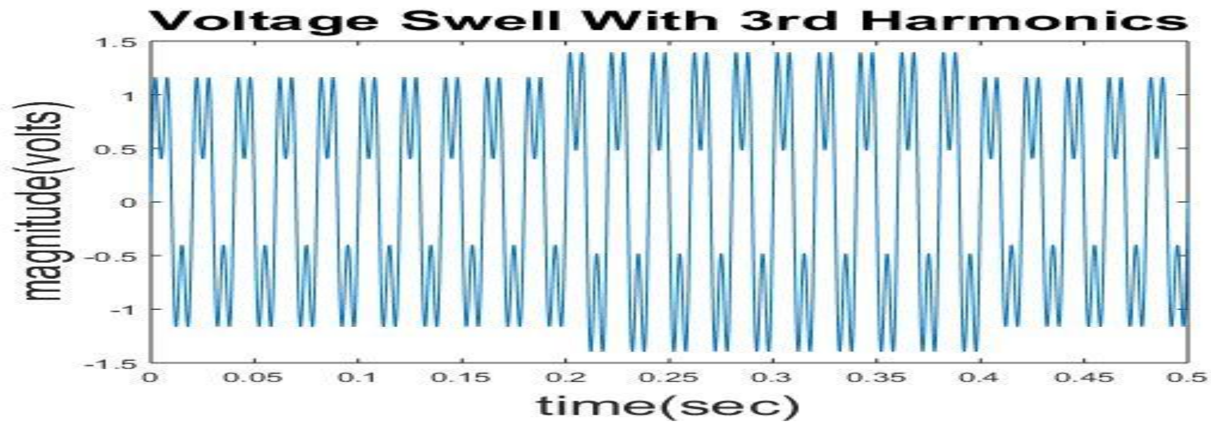

Figure 2.7 Voltage Swell With 3rd Harmonics

2.4 Decomposition Using Wavelet Transform

The above disturbances are decomposed into different levels through wavelet decomposition algorithm as shown in Figure 2.1 using equation 2.1 and equation 2.2. The unique deviation of every power quality disturbance from the original sinusoidal waveform is distinguished both in the approximate and detail coefficients. The different disturbances are examined with different levels. Generally, single or dual scale signal decomposition is satisfactory to differentiate disturbances from their background because the decomposed signals at lower scales have high time localization.

2.4.1 Voltage Sag

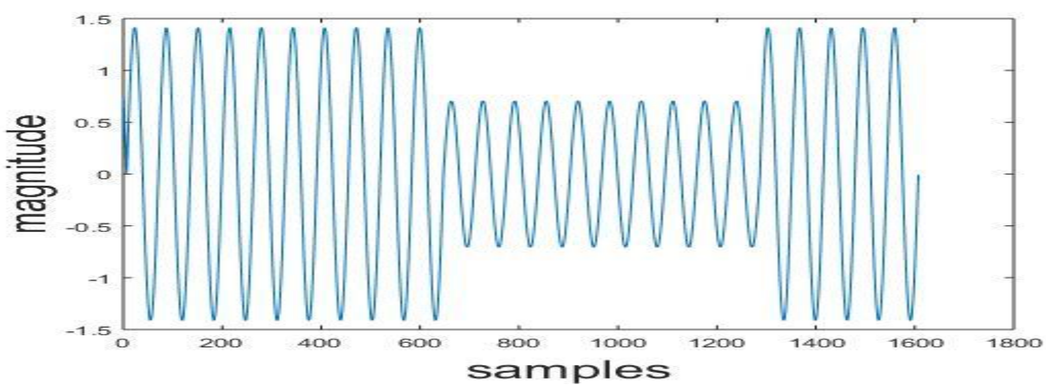

Figure 4.8(a) Approximate Signal Level 1

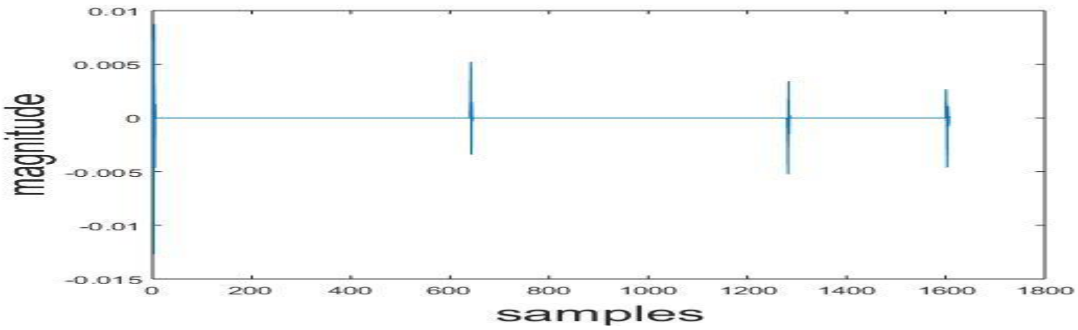

Figure 2.8 (b) Detail Signal Level 1

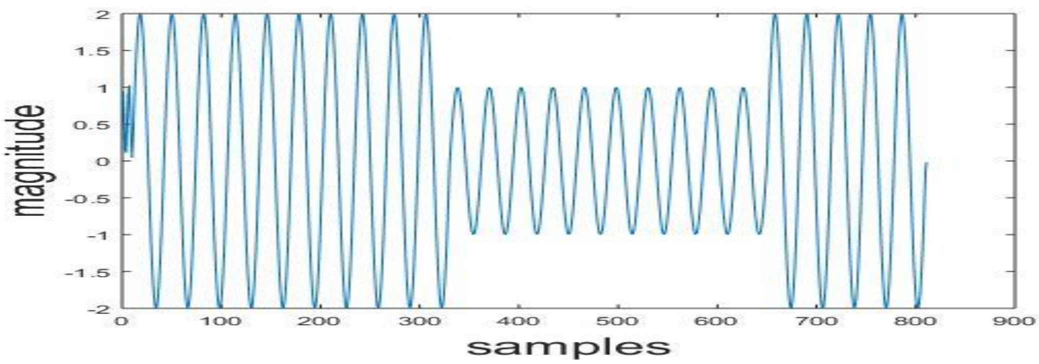

Figure 2.8 (c) Approximate Signal Level 2

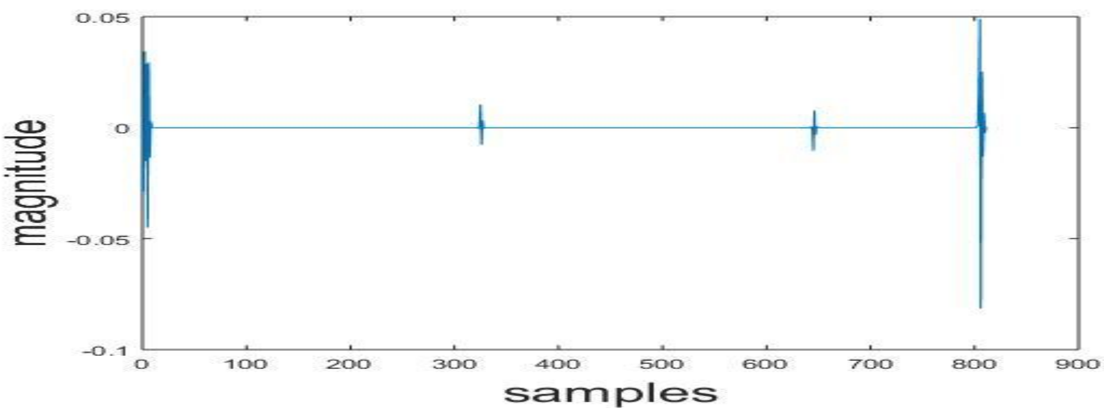

Figure 2.8 (d) Detail Signal Level 2

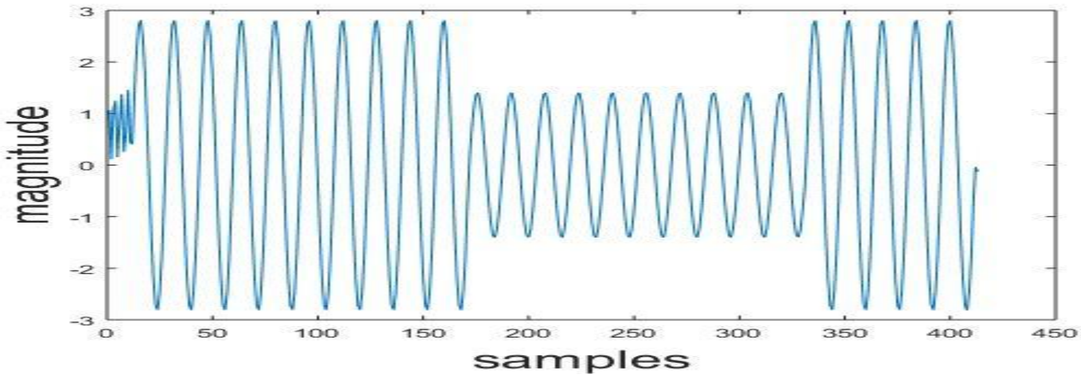

Figure 2.8 (e) Approximate Signal Level 3

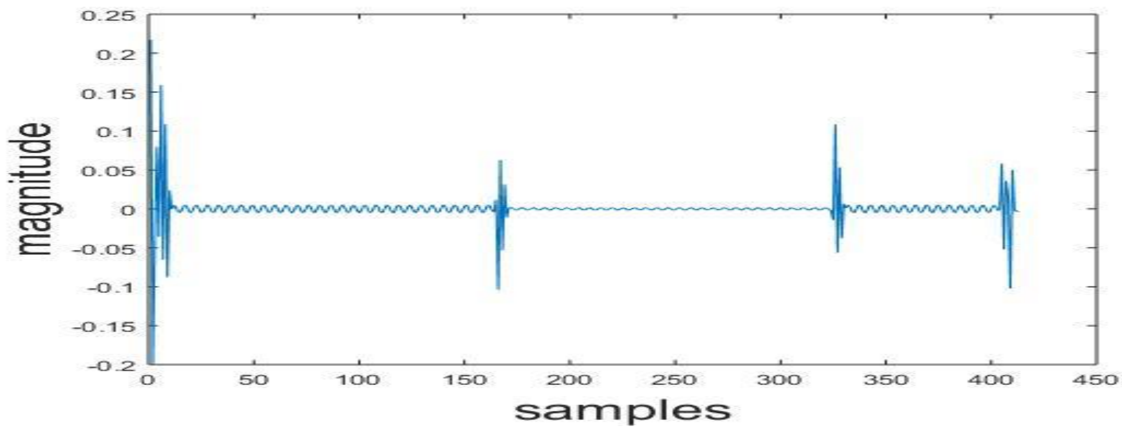

Figure 2.8 (f) Detail Signal Level 3

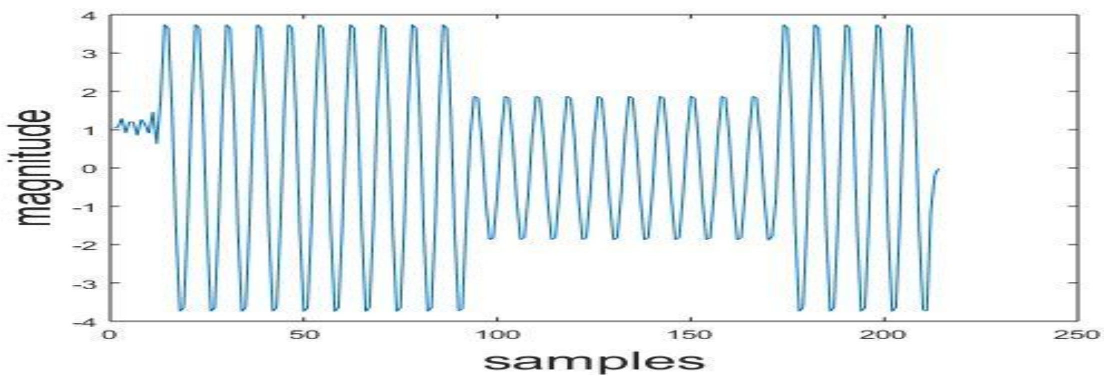

Figure 2.8 (g) Approximate Signal Level 4

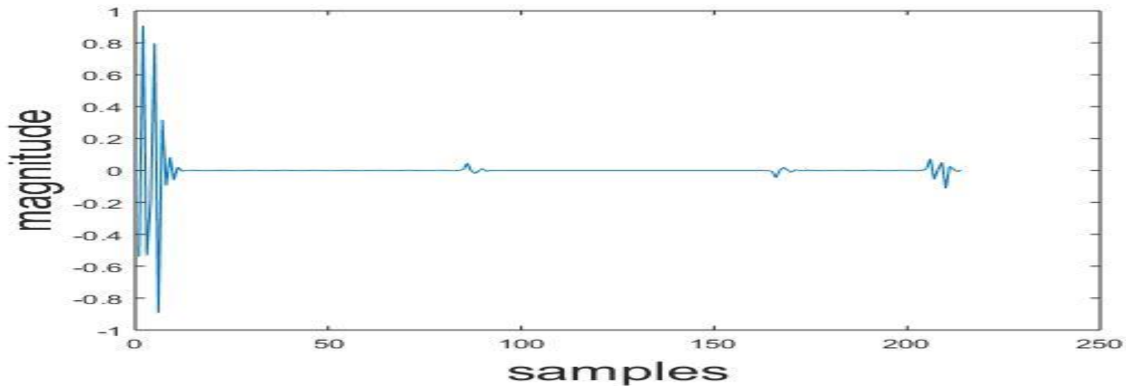

Figure 2.8 (h) Detail Signal Level 4

Reduction in nominal value of the waveform can be marked from the approximate and detail coefficient of level4 decomposition as shown in Figure 2.8(g) and Figure 2.8(h).

2.4.2 Voltage Swell

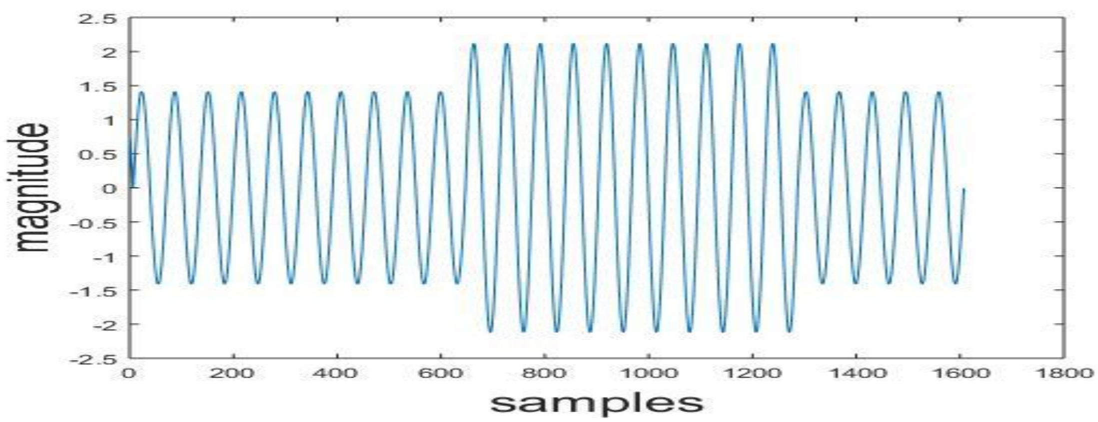

Figure 2.9 (a) Approximate Signal Level 1

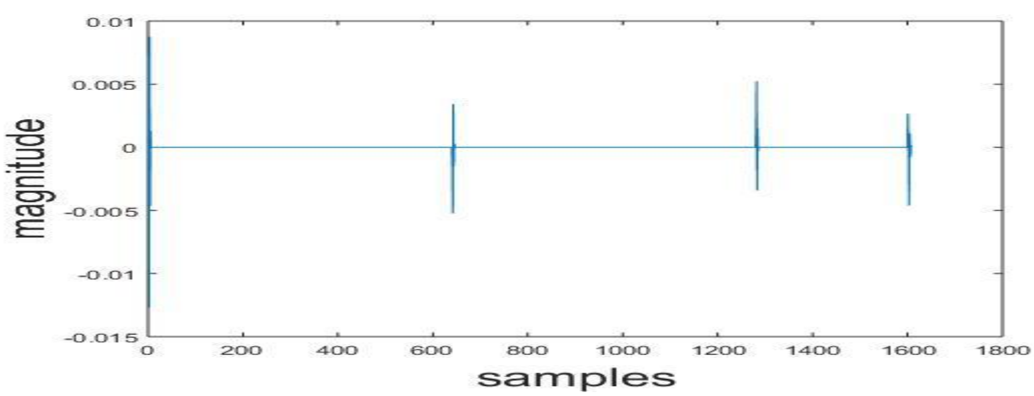

Figure 2.9 (b) Detail Signal Level 1

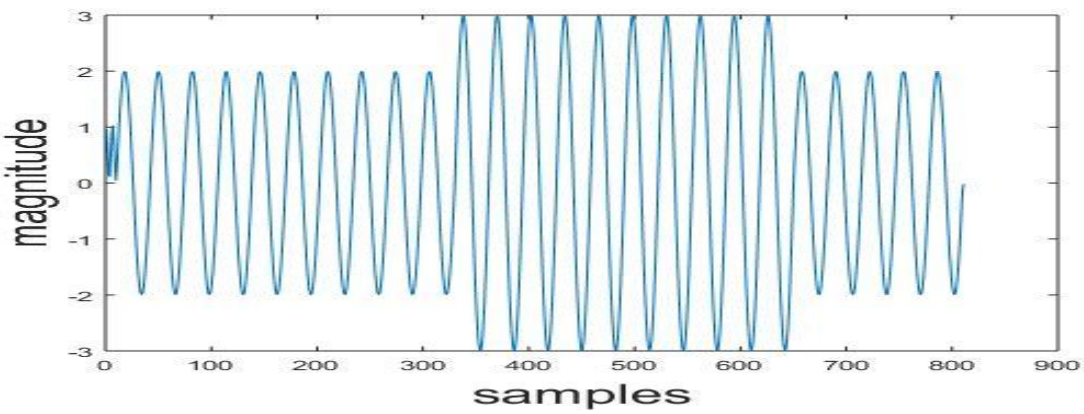

Figure 2.9 (c) Approximate Signal Level 2

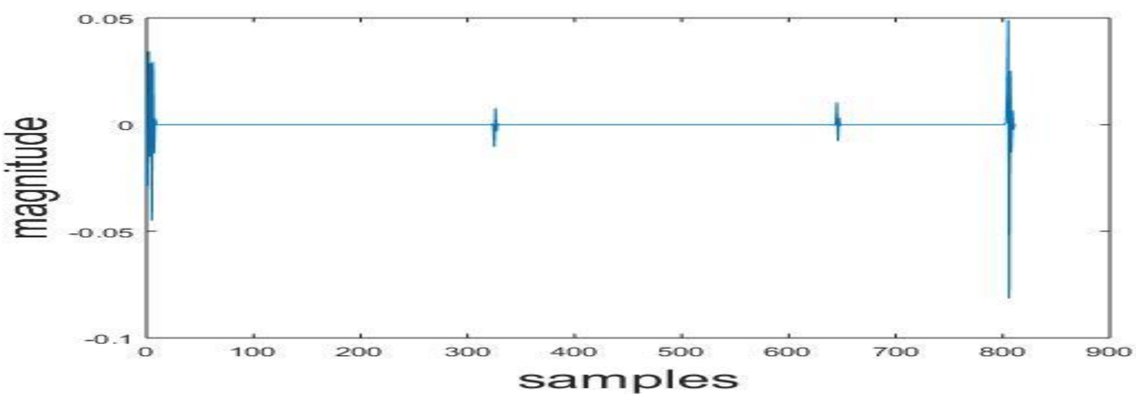

Figure 2.9 (d) Detail Signal Level 2

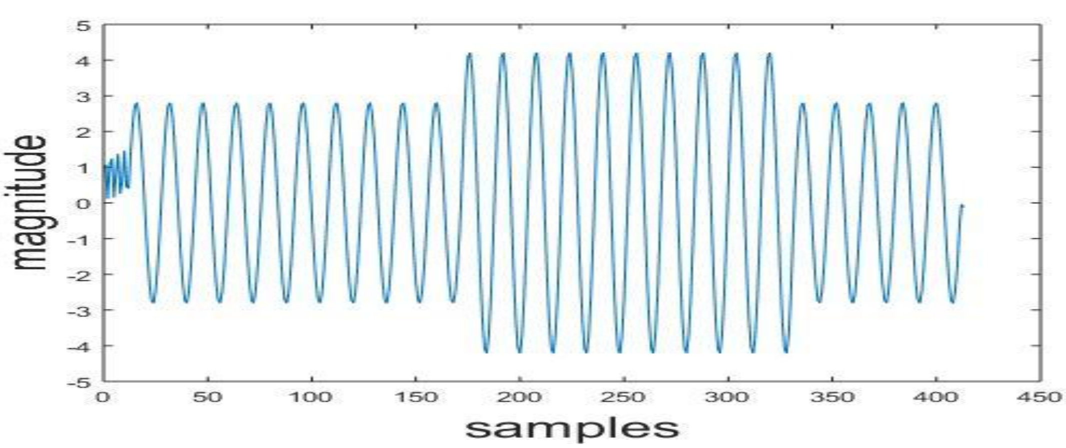

Figure 2.9 (e) Approximate Signal Level 3

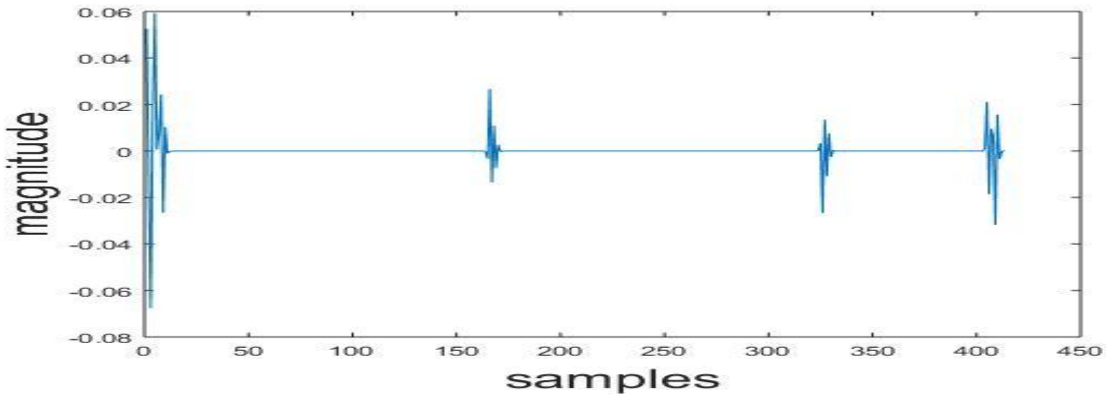

Figure 2.9 (f) Detail Signal Level 3

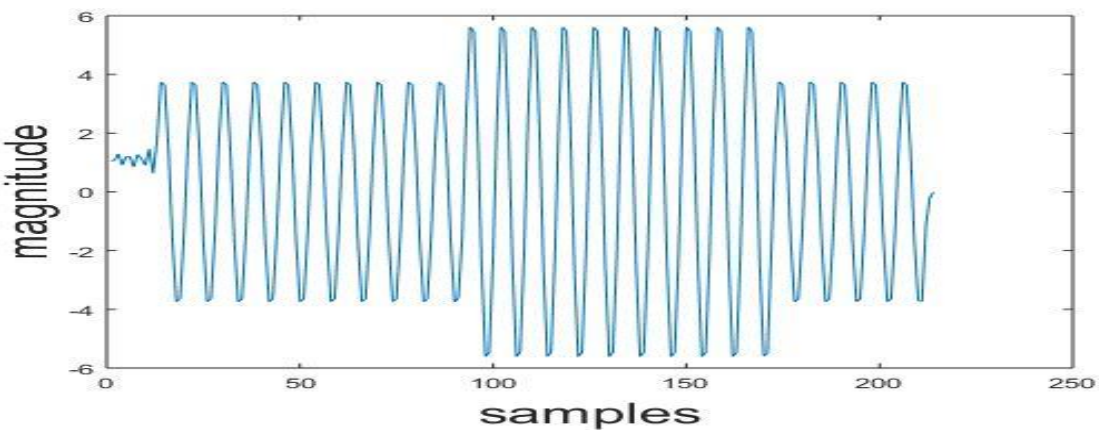

Figure 2.9 (g) Approximate Signal Level 4

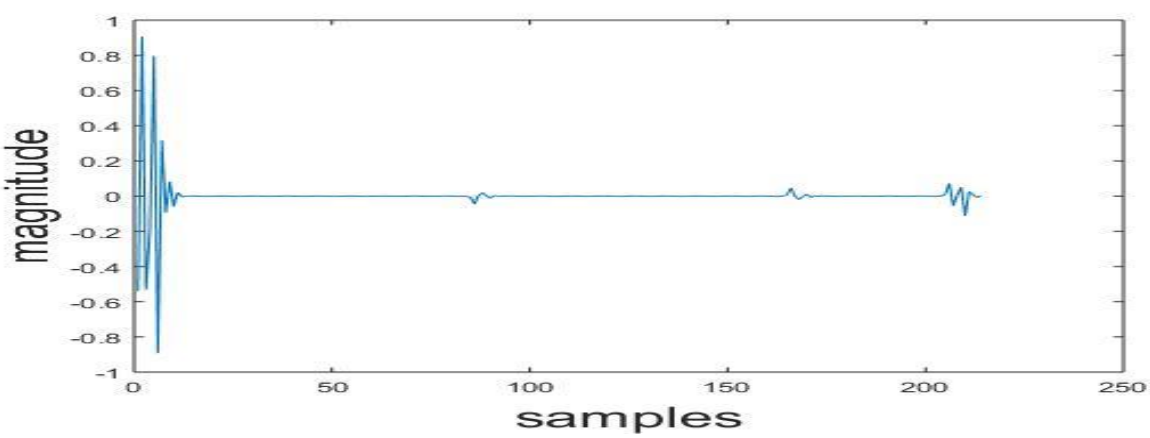

Figure 2.9 (h) Detail Signal Level 4

2.4.3 Voltage Interruption

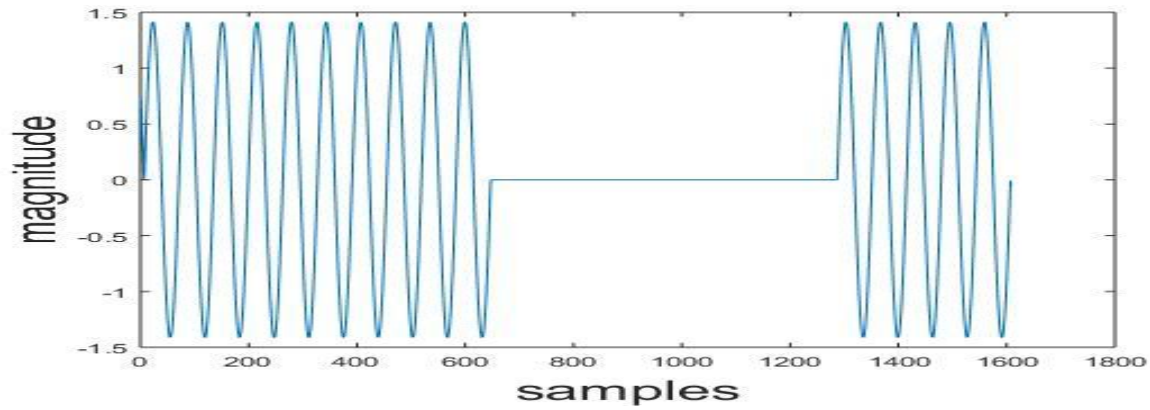

Figure 2.10 (a) Approximate Signal Level 1

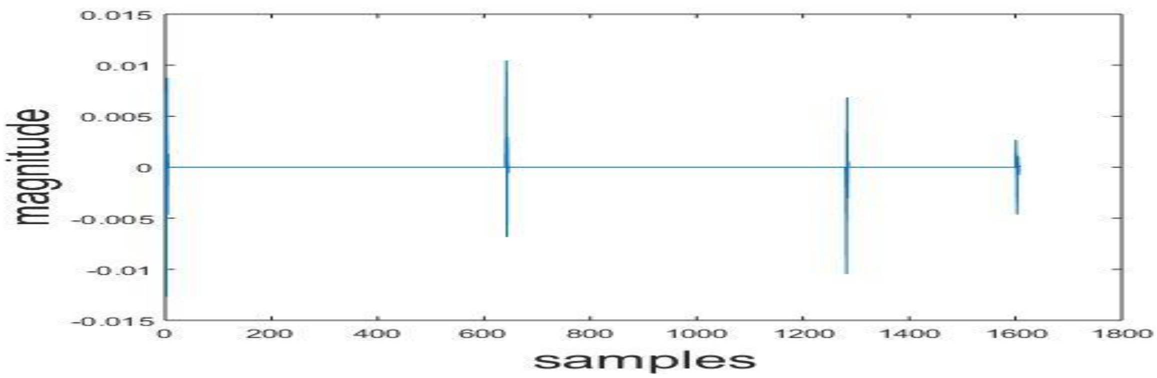

Figure 2.10 (b) Detail Signal Level 1

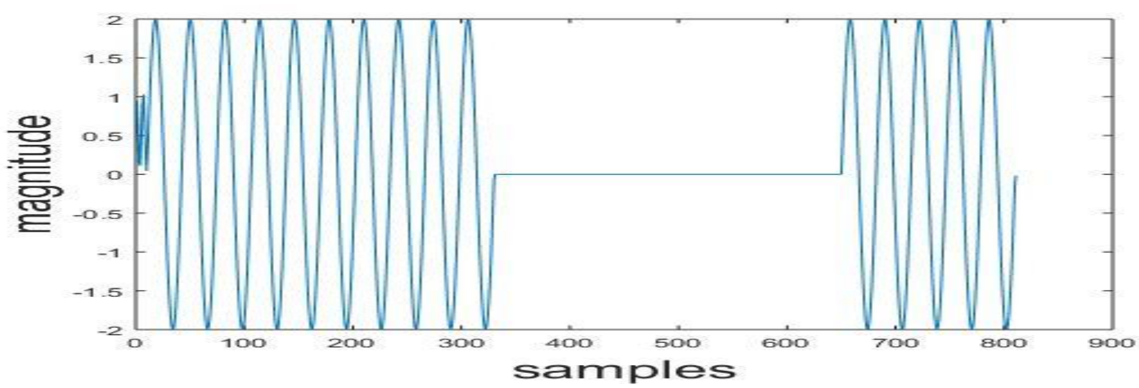

Figure 2.10 (c) Approximate Signal Level 2

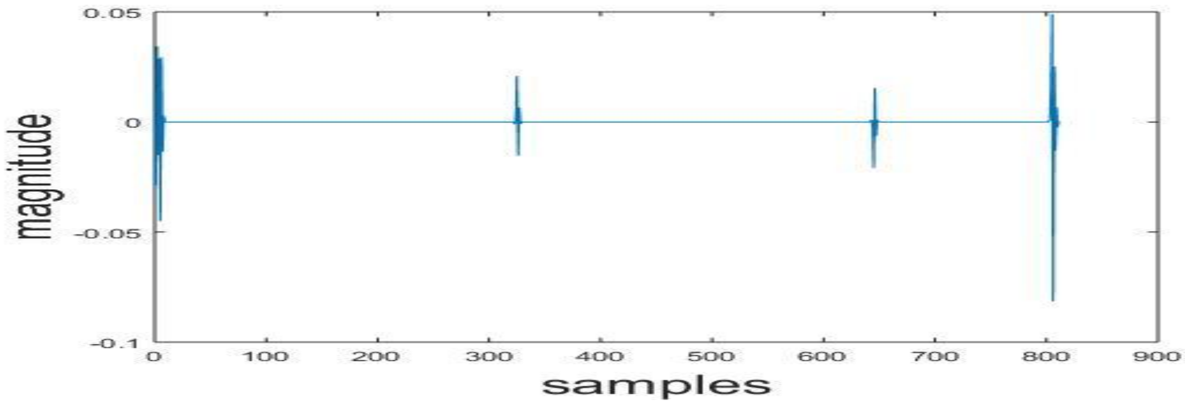

Figure 2.10 (d) Detail Signal Level 2

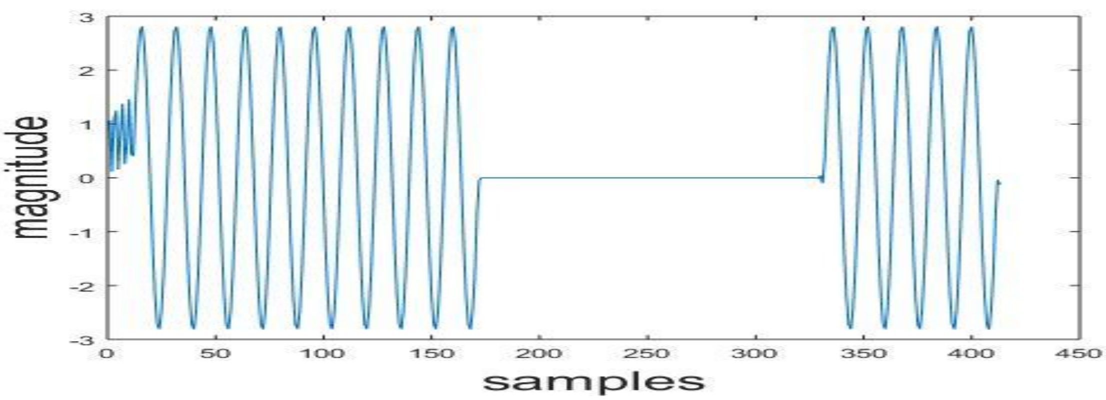

Figure 2.10 (e) Approximate Signal Level 3

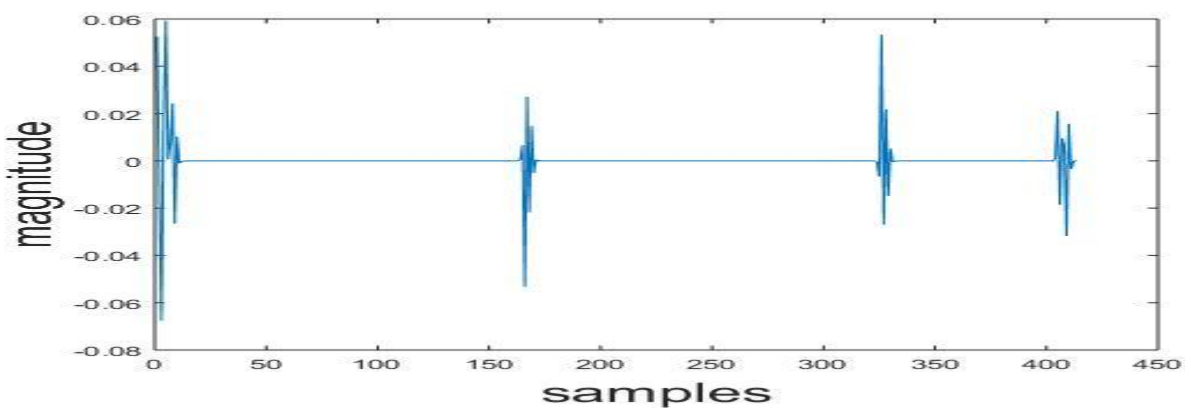

Figure 2.10 (f) Detail Signal Level 3

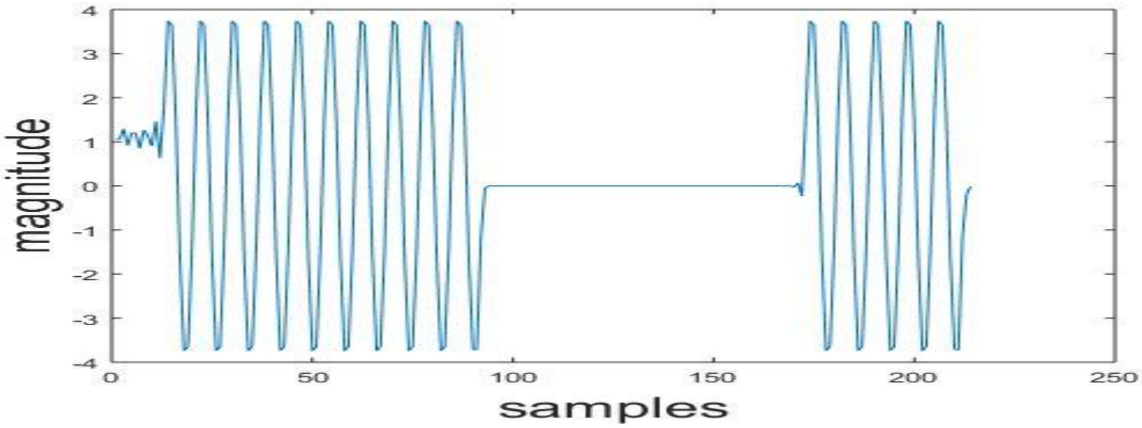

Figure 2.10 (g) Approximate Signal Level 4

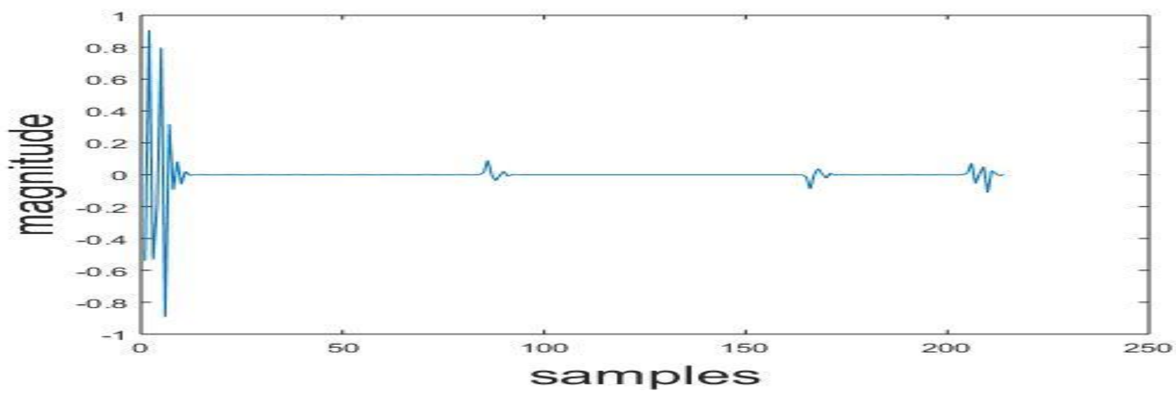

Figure 2.10 (h) Detail Signal Level 4

2.4.4 Voltage Sag With Harmonics

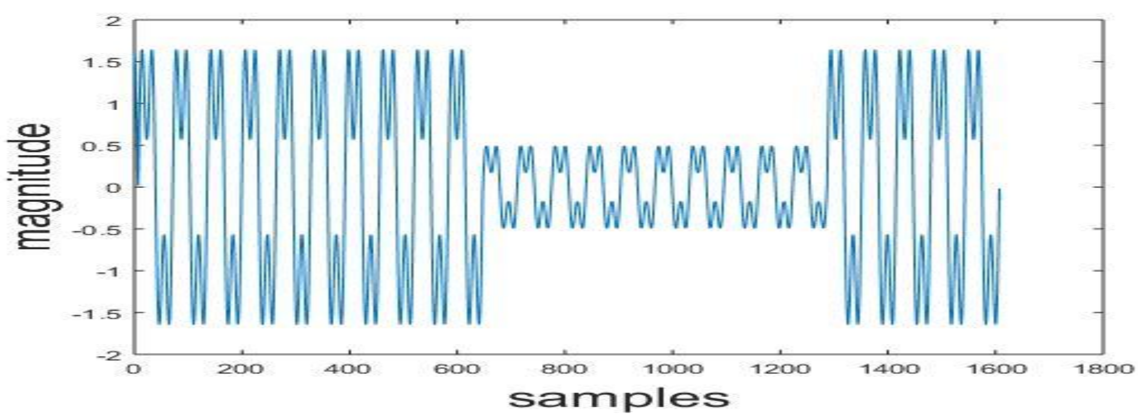

Figure 2.11 (a) Approximate Signal Level 1

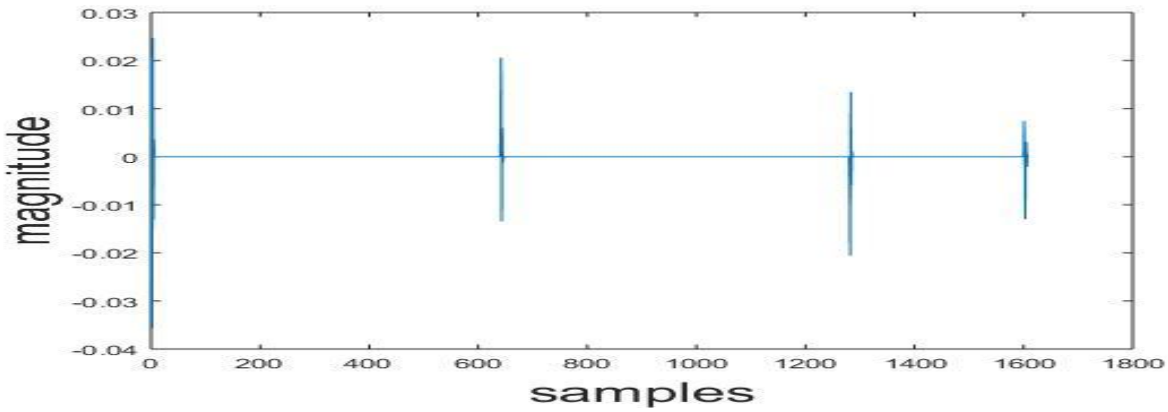

Figure 2.11 (b) Detail Signal Level 1

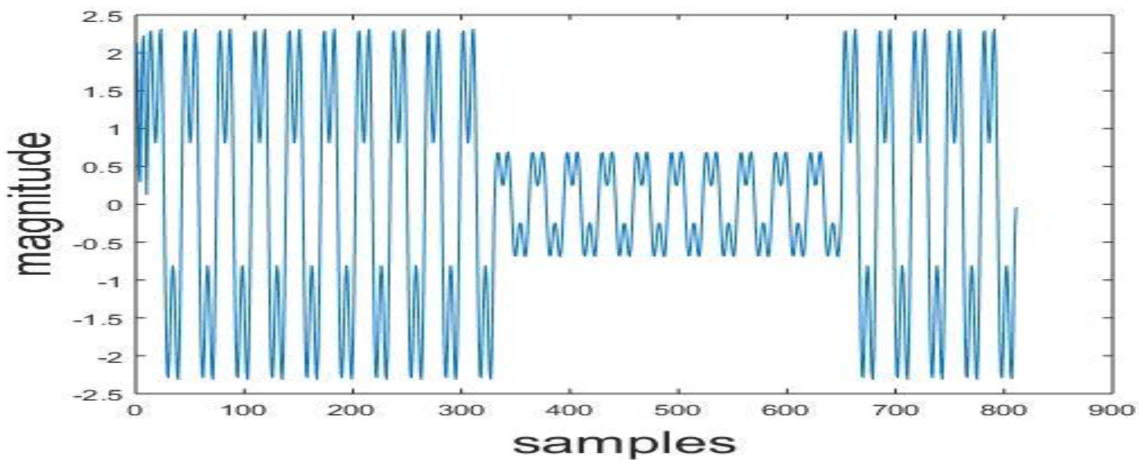

Figure 2.11 (c) Approximate Signal Level 2

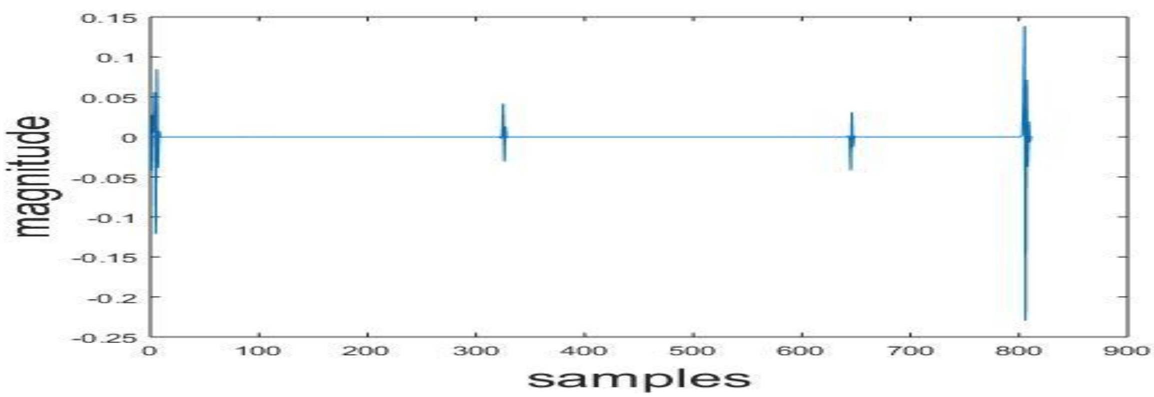

Figure 2.11 (d) Detail Signal Level 2

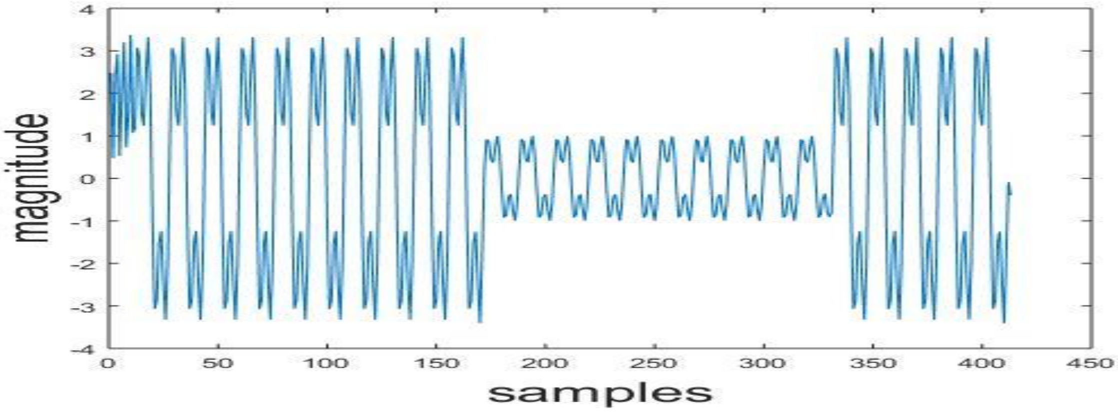

Figure 2.11 (e) Approximate Signal Level 3

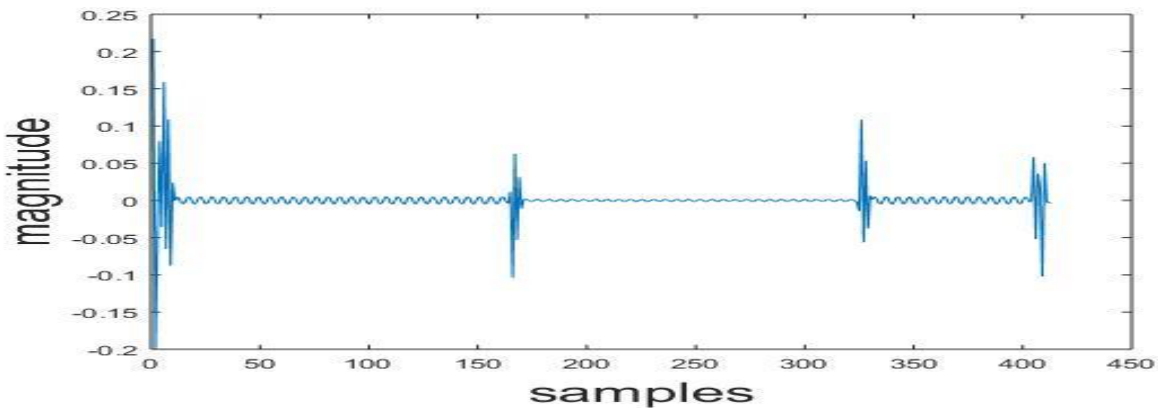

Figure 2.11 (f) Detail Signal Level 3

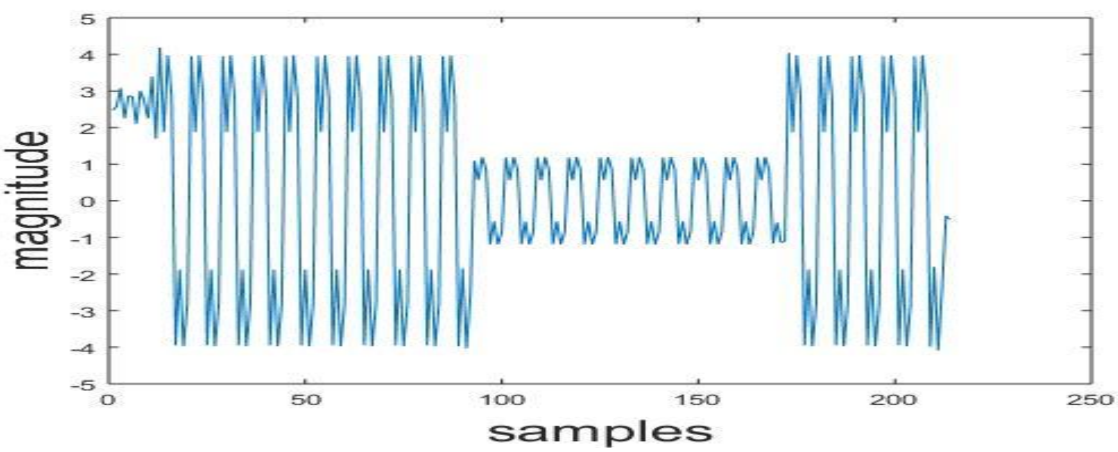

Figure 2.11 (g) Approximate Signal Level 4

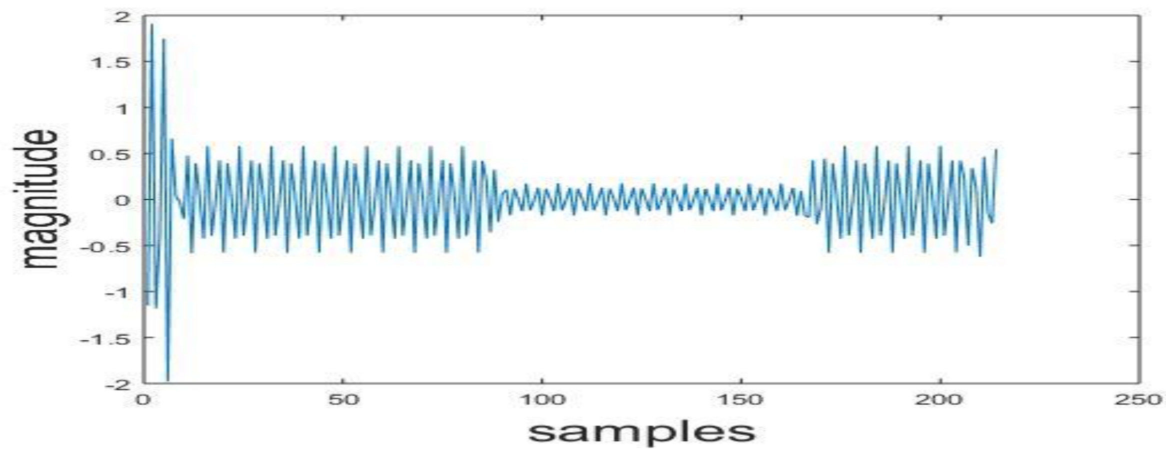

Figure 2.11 (h) Detail Signal Level 4

2.4.5 Voltage Swell With Harmonics

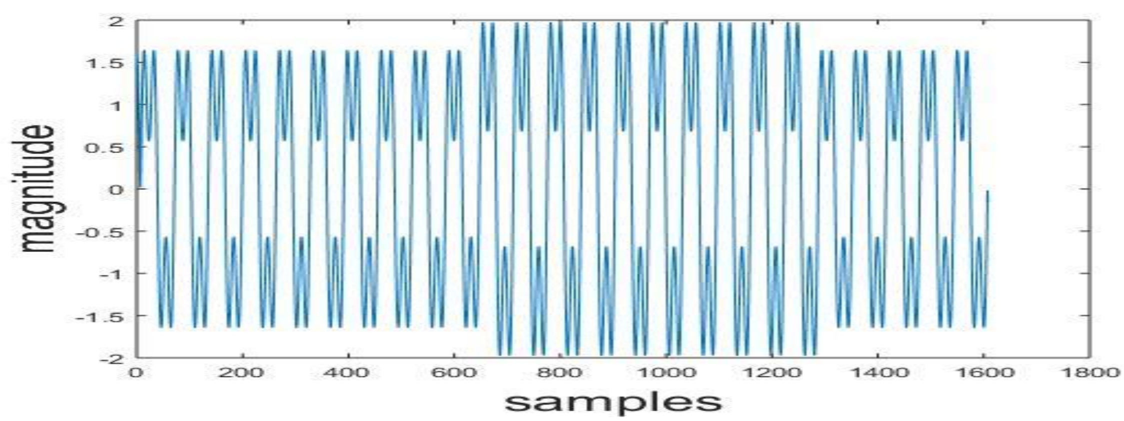

Figure 2.12 (a) Approximate Signal Level 1

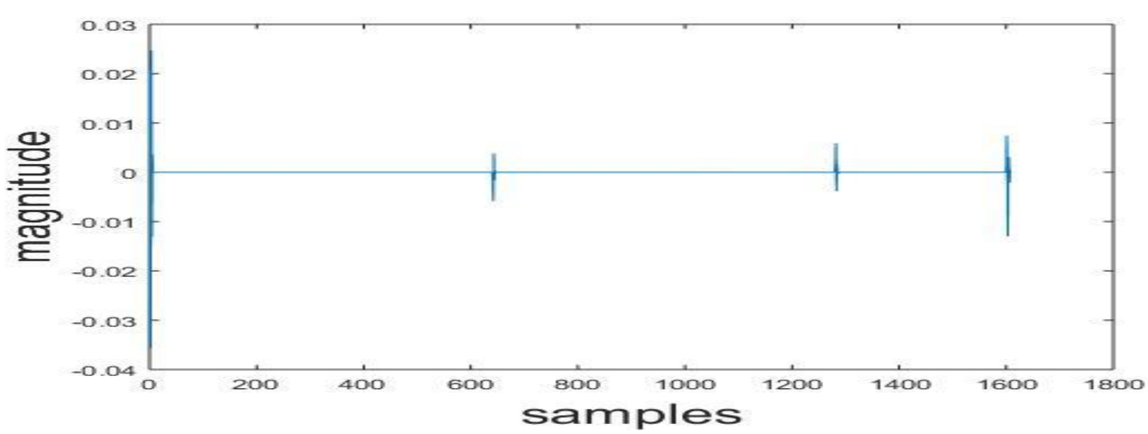

Figure 2.12 (b) Detail Signal Level 1

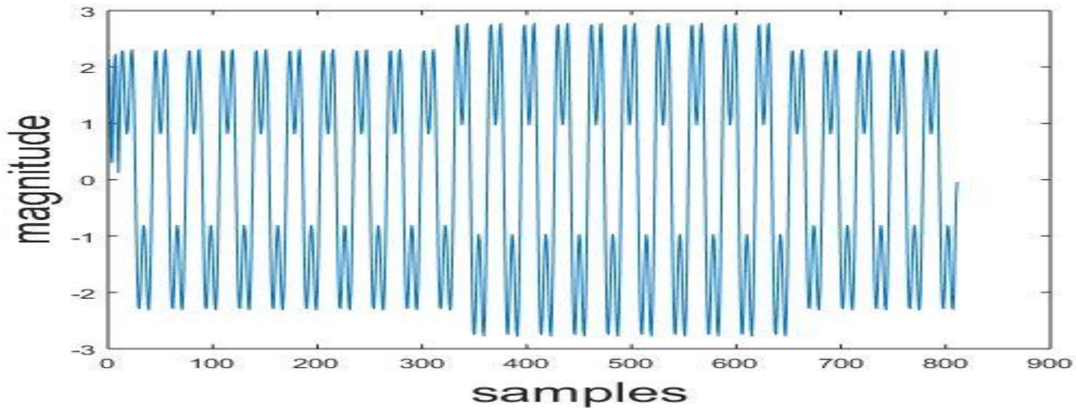

Figure 2.12 (c) Approximate Signal Level 2

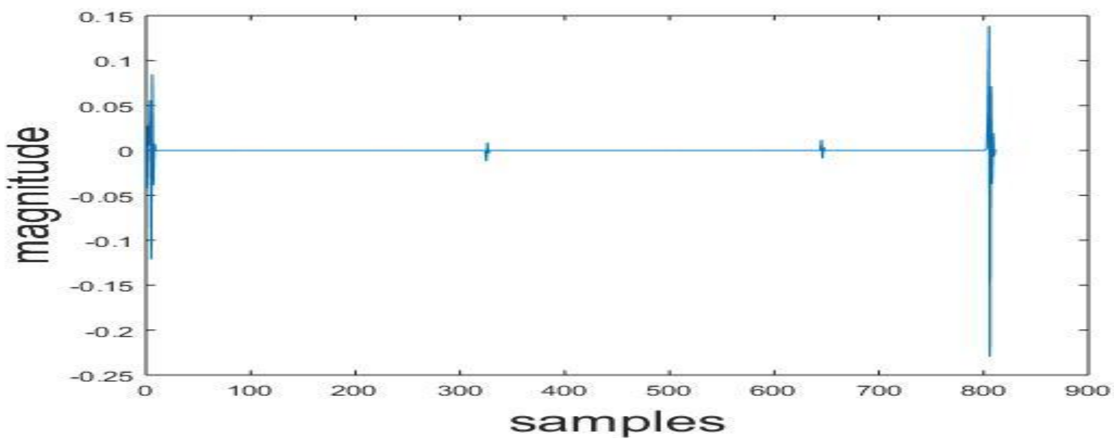

Figure 2.12 (d) Detail Signal Level 2

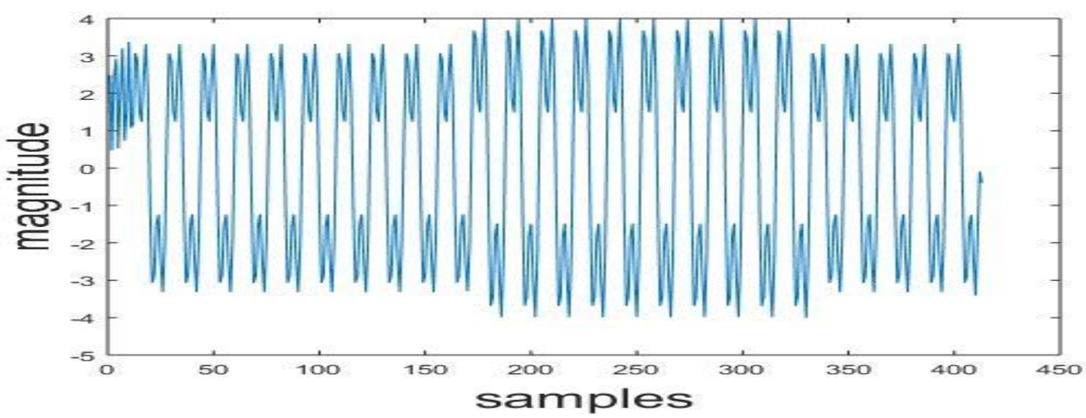

Figure 2.12 (e) Approximate Signal Level 3

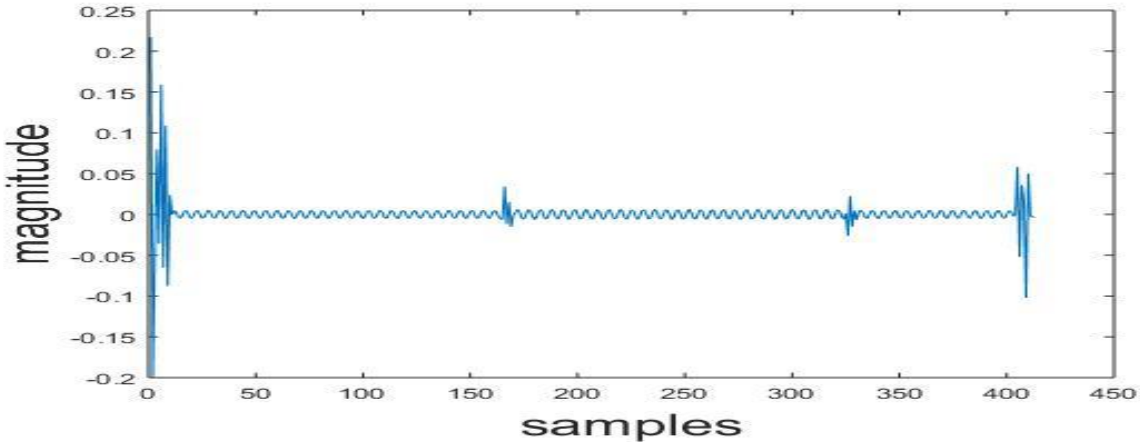

Figure 2.12 (f) Detail Signal Level 3

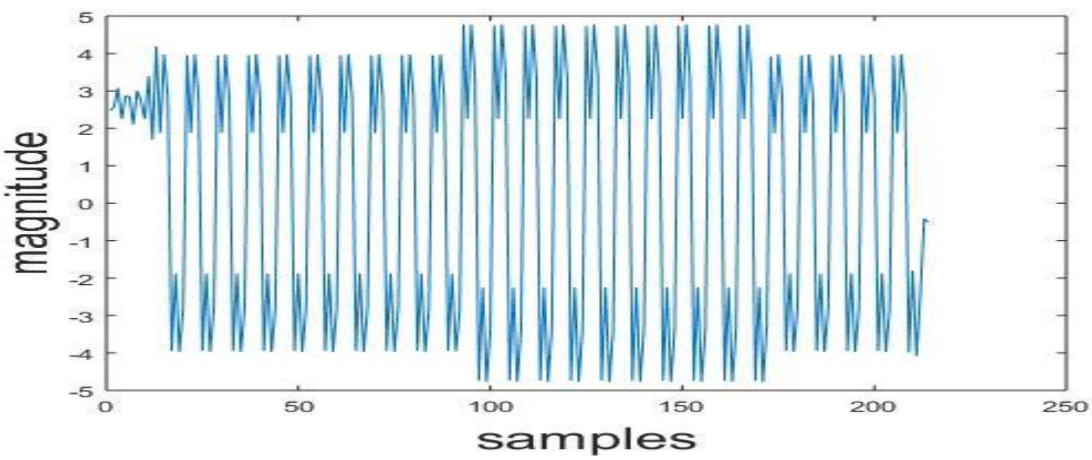

Figure 2.12 (g) Approximate Signal Level 4

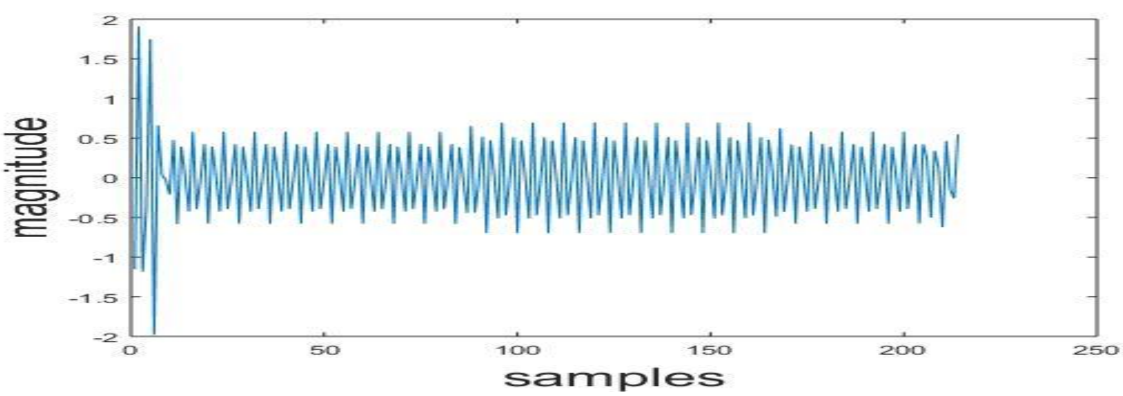

Figure 2.12 (h) Detail Signal Level 4

2.5 Detection in the presence of noise

The presence of noise in power quality disturbances creates a new obstruction for detection as it is tough to detect the exact location of disturbance in a high noisy environment with a low SNR(signal to noise ratio).The presence of noise likewise affects the classification accuracy as the feature vectors to be extracted for classification will also contain the noise contribution and the exact quantity of noise present are entirely dubious and hence de-noising of the disturbance is necessary for feature extraction and classification.

Chapter 3

Denoising of Power Quality Disturbances

3.1 Introduction

The best possible recognition i.e. the critical start-time and end-time of power quality (PQ) disturbances is a vital viewpoint in checking and locating of the fault instances so as to extract the features and develop a classification system. But the signal under processing is often polluted by noise, making the extraction of features a troublesome task, particularly if the noises have high frequency range which overlaps with the frequency of the disturbances. The performance of the classification system would be significantly degraded owing to the difficulty in distinguishing the noises and the disturbances, and also the feature vector to be extracted will contain noise. Subsequently it is a critical application of wavelet analysis in power system to de-noise power quality signals in order to detect and locate the disturbing points as the presence of noise in power quality events may degrade the classification accuracy.

3.2 De-nosing using WT

3.2.1 Steps involved in De-noising

Basically de-noising of signal consists of three steps:

- Decomposition: It consists of selecting a proper mother wavelet and deciding a level n up to which the signal S is to be decomposed using the selected mother wavelet. The level of decomposition n is selected as required and in this case it is selected as five.
- Thresholding: For each level from 1 to n, a threshold is selected and soft thresholding is applied to the detailed coefficients.
- Reconstruction: Wavelet reconstruction is computed based on the original approximation coefficients of level n and the modified detail coefficients of levels from 1 to n.

3.2.2 Thresholding based De-noising

In the first stage, the noise containing sinusoidal signal is decomposed by selected wavelet basic function “db8” up to 5 levels. Coefficients at every level are compared within this level and absolute maximum coefficient is stored to be the threshold value. The maximum coefficient is found as it shows the maximum noise characteristic. After processing, five detailed threshold values and one approximate threshold value will be stored for future signal denoising. In the next stage, the power quality disturbance signals polluted by noises are recorded as before. The disturbance signal is decomposed by the same wavelet basic function to the same level to generate wavelet transform coefficients. All coefficients at every level will be thresholded by the corresponding threshold value that is determined at the first stage. Any coefficients after the thresholding are the disturbance coefficients. Therefore after decomposition, the coefficients of the signal are greater than the coefficients of the noise, so we can find a suitable T as a threshold value. When the wavelet coefficient is smaller than the threshold, it is assumed that the wavelet coefficient is primarily created by the noise, so that coefficient is set to 0 and then discarded. When the wavelet coefficient is greater than the threshold, it is assumed that wavelet coefficient is mainly given by the signal, so that the coefficient is kept or shrinks to a fixed value, and then the signal denoised can be reconstructed through the new wavelet coefficients using wavelet transform.

The method can be modelled as shown below:

$S(n) = X(n) + \varepsilon.e(n)$ *Where* $n=0,1,2\ldots k-1$

$S(n)$ =Noisy Signal

$X(n)$=Useful Power Quality disturbance without noise

$e(n)$=The noise added to $X(n)$

3.2.3 Selection of Thresholding function

The thresholding on the DWT coefficients while applying wavelet based de-noising methods can be done using either hard or soft Thresholding. The hard threshold method is ineffective, and hard threshold function is not continuous making it mathematically difficult to deal with. The soft threshold function is continuous and overcomes the shortcomings of the hard thresholding. The soft thresholding is most appropriate for de-noising of PQ disturbances.

3.2.4 Selection of Thresholding rule

The selection of threshold value is crucial in wavelet based PQ signal de-noising. In this case, **Minimaxi** thresholding rule is used**.**

3.3 Results

3.3.1 De-noising of Sag disturbance

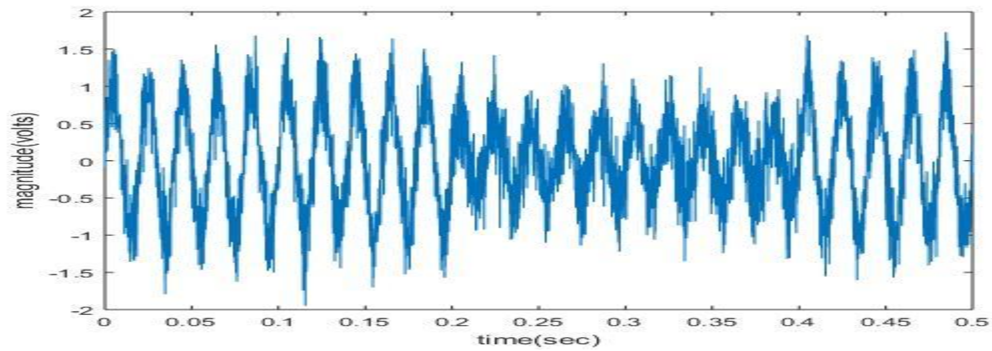

Figure 3.1 (a) Voltage Sag With Noise

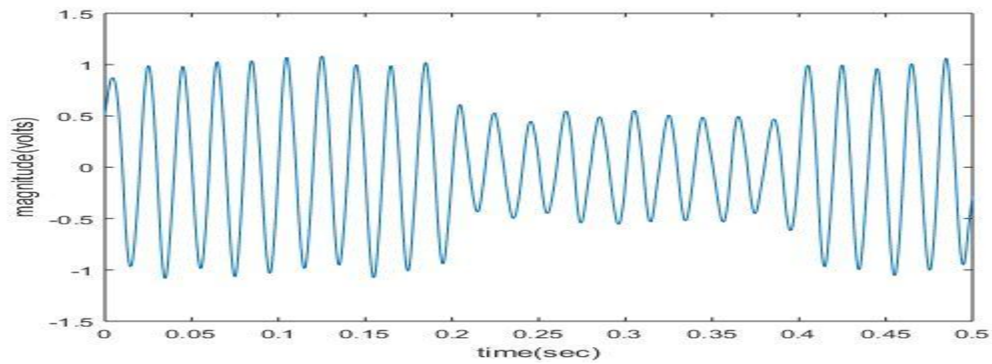

Figure 3.1 (b) De-noised Voltage Sag

3.3.2 De-noising of Swell disturbance

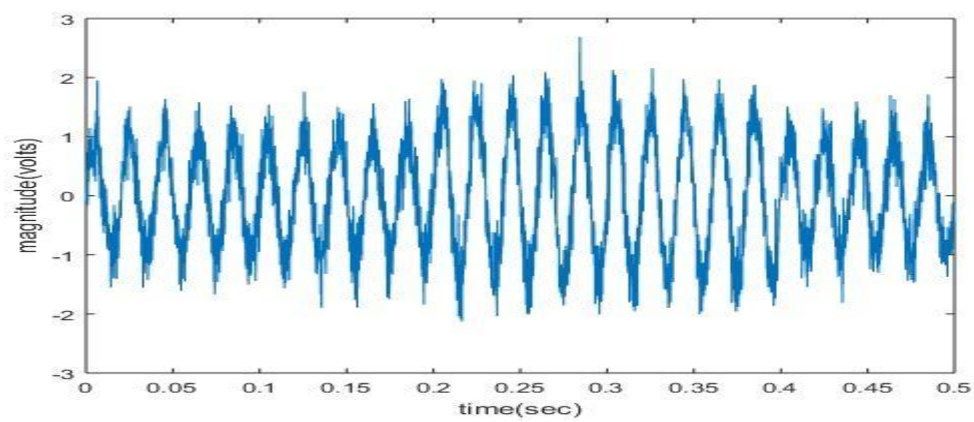

Figure 3.2 (a) Voltage Swell With Noise

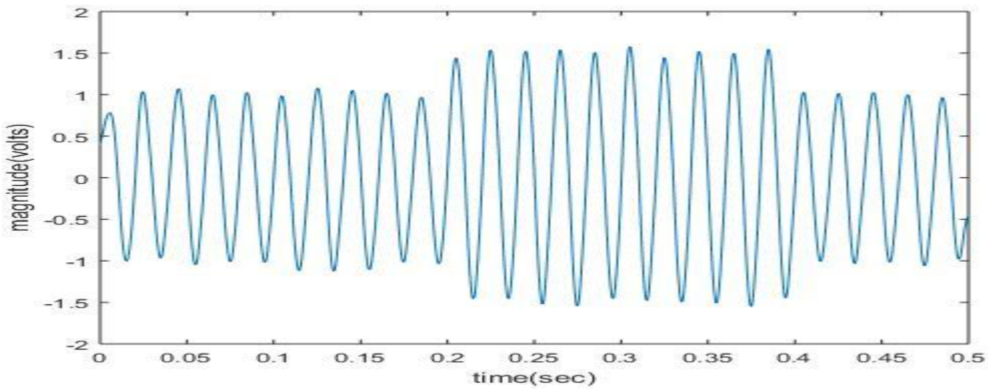

Figure 3.2 (b) De-noised Voltage Swell

3.3.3 De-noising of Interruption disturbance

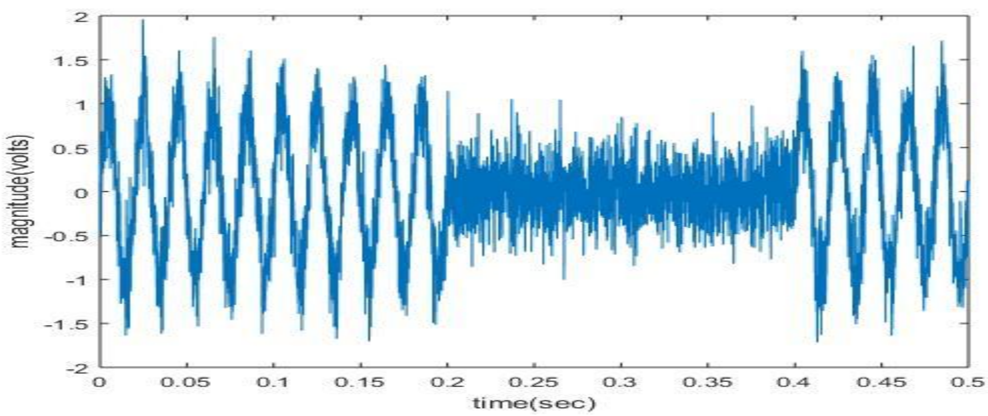

Figure 3.3 (a) Voltage Interruption With Noise

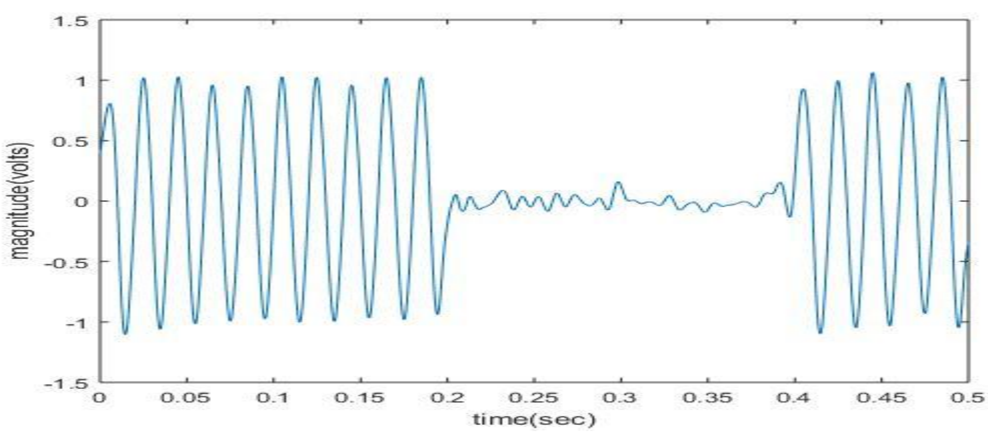

Figure 3.3 (b) De-noised Voltage Interruption

Figures 3.1(a), 3.2(a) and 3.3(a) show the disturbance in the presence of noise. Figures 3.1(b), 3.2(b) and 3.3(b) show the de-noised signal after using wavelet based de-noising methods. It can be seen that the de-noised signal is very similar to the originally simulated signal making this method a very effective one.

Chapter 4

Feature Extraction

4.1 Introduction

The feature extraction is a vital undertaking in outlining a monitoring framework which will show the kind of PQ disturbance happening in the power system. A database is to be arranged taking into account some unique parameters which will help in recognizing diverse PQ disturbances with the slightest measure of uncertainty. In this work after de-noising of PQ occasions, total harmonic distortion (THD) and Energy of the signal are utilized as the two unique parameters for feature extraction and getting the database ready. These databases are utilized as a contribution to the fuzzy expert framework for the purpose of classification and furthermore these databases are required to prepare the neural system so that a power quality disturbance (PQD) discovery framework can be displayed.

4.2 Feature Vector

4.2.1 Energy

Parseval's theorem is used to compute the energy of the signal. The approximate and detailed coefficients of the wavelet decomposed signal can be used to calculate the energy of the signal as given by the equation 4.1.

$$E = \sum_{k} |\, C_j(k)|^2 + \sum_{j=1}^{I} \sum_{k} |D_j(k)|^2 \tag{4.1}$$

Where $C_j(k)$: approximate coefficient at j^{th} level

$D_j(k)$: detail coefficient at j^{th} level

4.2.2 Total Harmonic Distortion

It can be defined as the summation of all the harmonic components that are present in the signal compared to the fundamental component of the signal.

$$THD = \frac{\sqrt{\frac{1}{N_j}\sum_n[cD_j(n)]^2}}{\sqrt{\frac{1}{N_6}\sum_n[cA_6(n)]^2}} \tag{4.2}$$

Where N_j : number of detail coefficients at scale j

4.3 Design of database of different PQ disturbances

A database of Energy and THD of different PQ disturbances based on equation (4.1) and equation (4.2) is obtained. Diverse PQ disturbances with diverse magnitude of fault are generated and considered for feature extraction.

4.3.1 Voltage Sag

Table 4.1 Feature Vector for Voltage Sag

Magnitude of Disturbance(%)	THD	Energy
10	0.808144743176508	1844.66850778542
19	0.845779415110629	1764.95676837728
31	0.830623536070066	1643.65692948336
40	0.854810607338440	1592.10945066954
49	0.837725528909451	1536.99913110759
61	0.913815401239697	1417.62366303698
70	0.843570293576896	1432.17796992267
79	0.863493674747566	1448.80086289777
88	0.882097514234533	1385.72022334068

4.3.2 Voltage Sag With Harmonics:

Table 4.2 Feature Vector for Voltage Sag with Harmonics

Magnitude of Disturbance(%)	THD	Energy
10	1.13917618000961	2889.93010768245
19	1.19295647772904	2582.06332512933
31	1.13913653916371	2418.16929979591
40	1.10300990778028	2506.55659828315
49	1.18085351797349	2111.55666196798
61	1.11594526320815	2265.59645930541
70	1.21410406643884	2025.81061580753
79	1.05939224919283	2255.16186745954
88	1.05186853814774	2187.73905988913

4.3.3 Voltage Swell:

Table 4.3 Feature Vector for Voltage Swell

Magnitude of Disturbance(%)	THD	Energy
110	0.78793826885297	2173.64740397426
119	0.745234822452356	2347.62035058281
131	0.757809776640451	2503.83566022815
140	0.759099385250080	2572.59633442265
149	0.734448530546236	2821.35116384528
161	0.686337022088169	3011.92749816679
170	0.694032548883071	3227.66712050837
179	0.674345134858602	3520.73727348724
188	0.668031966719505	3794.44109798532

4.3.4 Voltage Swell with Harmonics:

Table 4.4 Feature Vector for Voltage Swell with Harmonics

Magnitude of Disturbance(%)	THD	Energy
110	1.12853028491160	3025.91434544454
119	1.11896828356351	3371.42806472994
131	1.18422038178371	3356.87781614119
140	1.06787837137104	4008.40818260186
149	1.11562019100055	4050.40115551218
161	1.14215233117137	4368.32549571182
170	1.12814103107087	4673.80303789524
179	1.12115532241332	4980.66058929091
188	1.07375713505606	5340.75724782807

4.3.5 Voltage Interruption:

Table 4.5 Feature Vector for Voltage Interruption

Magnitude of Disturbance(%)	THD	Energy
8	0.855913767254355	1431.01619679477
7.1	0.875106038057038	1392.25395021053
5.9	0.913392171662656	1323.86439354752
5	0.928962913999632	1357.55893534302
4.1	0.872269411869473	1418.08063654238
2.9	0.866270116012695	1437.66018915256
2	0.924009544389305	1373.70733129085
1.1	0.886223776699557	1388.76994613935
0.2	0.881898950743905	1379.63205207057

Chapter 5

Modeling of PQD detection system using Multilayer Feedforward Network

5.1 Introduction

The work on Neural Networks (NN) was motivated from the way the human cerebrum works. Our mind is an exceedingly non-linear, intricate and parallel PC like gadget. It has the capacity to sort out its basic constituents known as neurons, in order to complete certain calculations much speedier than the speediest advanced PC in presence today. This capacity of our mind has been used into handling units to exceed expectations in the field of artificial intelligence. The hypothesis of cutting edge neural networks was started by the spearheading works done by Pitts (a Mathematician) and McCulloh (a specialist) in 1943. This Chapter shows the endeavor at demonstrating the power quality disturbance (PQD) discovery framework utilizing Multilayer Feedforward Neural Network (MFNN).

5.2 Multilayer Feedforward Network

5.2.1 MFNN Structure

ANN's are enormously parallel-interconnected networks of straightforward components expected to connect with this present reality similar to the natural sensory system. They offer an unique plan based programming point of view and display higher figuring speeds contrasted with other traditional strategies. ANNs are portrayed by their topology, that is, the quantity of interconnections, the node qualities that are arranged by the sort of nonlinear components utilized and the sort of learning techniques utilized. The ANN is made out of a sorted out topology of Processing Elements (PEs) called neurons. In Multilayer Feedforward Neural Network (MFNN) the PEs are organized in layers and just PEs in adjoining layers are associated. The MFNN structure utilized as a part of this postulation comprises of three layers, specifically, the input layer, the hidden layer and the output layer.

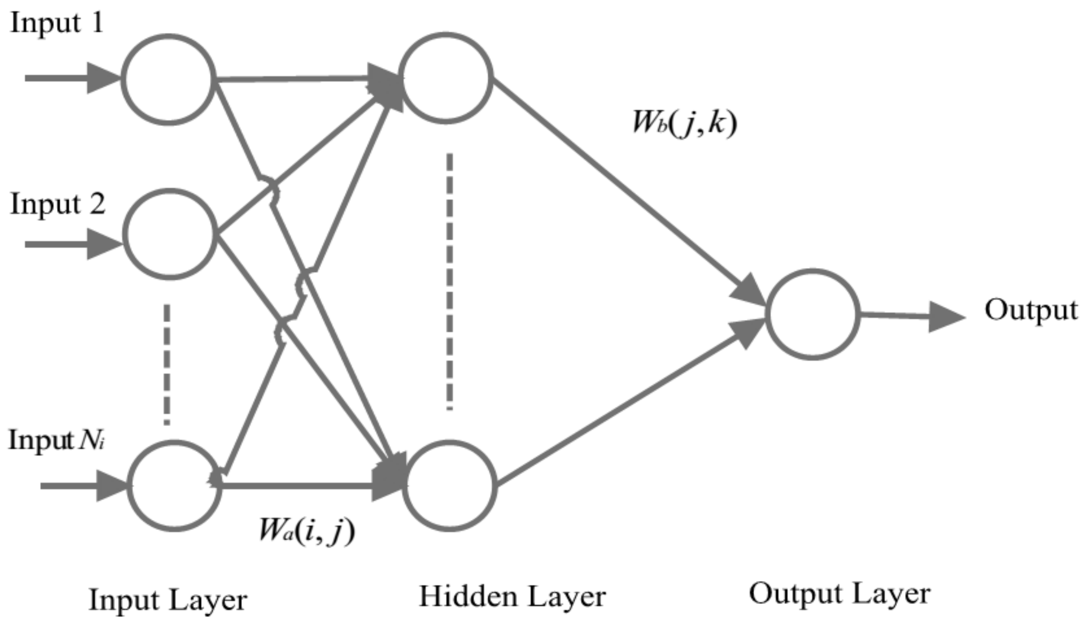

Figure 5.1 Multilayer Feedforward Network

Here the input layer comprises of Ni neurons corresponding to the Ni inputs. The number of output neurons are chosen by the quantities of anticipated parameters. The Back Propagation Algorithm (BPA) is used to train the network. The sigmoidal function represented by equation(5.1) is utilized as the activation function for all the neurons aside for those in the input layer.

$$S(x) = {}^{1}\!/_{1 + e^{-x}} \qquad (5.1)$$

5.2.2 Back Propagation Algorithm

It is a strategy for managed learning that can be envisioned as a speculation of the delta standard. Back propagation requires that the activation function which is utilized by the simulated neurons must be differentiable. The back propagation learning algorithm can be separated into two stages: propagation and weight update.

Stage 1: Propagation

Every propagation module involves the accompanying strides:

1. Forward propagation of a training data pattern's input contribution through neural system keeping in mind the end goal to create the propagation's output activations.

2. Backward propagation of the propagation's output activations through the neural system by utilizing training pattern's target to produce the deltas of all output and hidden neurons.

Stage 2: Weight upgrade For each weight-neural connection:

1. To find the gradient of the weight, multiply the output delta and the input activation.

2. Acquire the weight the other way of the inclination by subtracting a proportion of it from the weight.

This proportion has an effect on the rate and nature of learning; it is along these lines called the learning rate. The sign of the gradient of a weight implies that where error is expanding, as a result of this the weight must be updated the other way.

5.2.3 Choice of Hidden Neurons

The decision of ideal number of hidden neurons, N_h is the most intriguing and testing viewpoint in outlining the MFNN. There are different schools of thought in choosing the estimation of N_h. Simon Haykin has determined that N_h ought to lie somewhere around 2 and ∞. Hecht-Nielsen utilizes ANN elucidation of Kolmogorov's hypothesis to touch base at the upper bound on the N_h for a solitary hidden layer system as 2(Ni+1), where Ni is the quantity of input neurons. A vast estimation of N_h may diminish the training error connected with the MFNN, however at the expense of expanding the computational intricacy and time.

5.2.4 Normalization of Input-Output data:

The input and the output information are standardized before being handled in the system. In this plan of standardization, the most extreme estimations of the input and output vector parts are resolved as follows:

$$n_{i,max} = \max(n_i(p))\ ;\ p = 1,\ldots\ldots, N_p,\ i = 1,\ldots\ldots, N_i \qquad (5.2)$$

Where N_i is the number of patterns in the training set

$$o_{k,max} = \max(o_k(p));\ p = 1,\ldots\ldots N_p,\ k = 1,\ldots\ldots N_k \qquad (5.3)$$

Where N_k is the number of neurons in the output layer

$$n_{i,nor} = \frac{n_i(p)}{n_{i,max}} \tag{5.4}$$

$$o_{k,nor} = \frac{o_i(k)}{o_{i,max}} \tag{5.5}$$

5.2.5 Choice of ANN parameters

The momentum factor, α_1 and learning rate, η_1 have an exceptionally significant impact on the learning pace of the BPA. The BPA gives an approximation to the direction in the weight space figured by the technique for steepest descent strategy. On the off chance that the assumption of η_1 is considered small, the outcome is moderate rate of learning, while if the estimation of η_1 is too huge so as to accelerate the rate of learning, the MFNN may get to be temperamental (oscillatory). A straightforward strategy for expanding the rate of learning without making the MFNN temperamental is by including the momentum variable α_1. Ideally, the estimations of η_1 and α_1 ought to lie somewhere around 0 and 1.

5.2.6 Weight Update Equations

Update of weights between the hidden layer and the output layer are based on the equation (5.6) as follows:

$$w_b(j,k,m+1) = w_b(j,k,m)+\eta_1*\delta_k(m) *S_b(j) + \alpha_1 [w_b(j, k, m) - w_b(j, k, m-1)] \tag{5.6}$$

here m is the number of iterations, j varies from 1 to N_h and k varies from 1 to N_k. $\delta_k(m)$ is the error for the k^{th} output at the m^{th} iteration. $S_b(j)$ is the output from the hidden layer.

Similarly, the weights between the hidden layer and the input layer are updated as follows:

$$w_a(i,j,m+1)=w_a(i,j,m)+\eta_1*\delta_j(m)*S_a(i) + \alpha_1 [(w_a(i, j, m) - w_a(i, j, m-1)] \tag{5.7}$$

here i varies from 1 to N_i as there are N_i inputs to the network, $\delta_j(m)$ is the error for the j^{th} output after the m^{th} iteration and $S_a(i)$ is the output from the first layer.

5.3 Modeling of PQD using MFNN

This section points out the endeavor at displaying a detection framework for power quality disturbances utilizing MFNN. This model predicts the rate of disturbances in different power quality occasions as an element of Energy and THD of various power quality occasions. The system is given both input information and desired reaction and is prepared in a supervised way utilizing the back propagation algorithm. The back propagation algorithm performs the input to output mapping by making weight association alteration taking after the error between the calculated output esteem and the desired output reaction. The preparation stage is over after a progression of cycles. In every cycle, output is compared with desired reaction and a match is acquired.

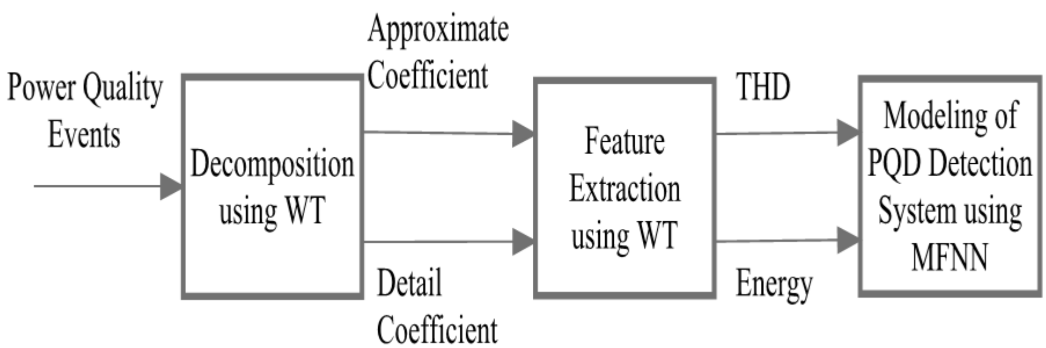

Figure 5.2 Processes involved in Modeling of PQD Detection system

In this model, the quantity of input parameters is two, that is, the energy and THD of various power quality disturbance. The rate of disturbance is to be anticipated. Since, the input parameters are two, the estimation of N_i is two for this model. Moreover, since the output parameter is just one, the estimation of N_k is one. The quantity of hidden neurons are taken as six.

Table 5.1 Input- Output Dataset

Serial Number	Type Of Disturbance	Energy	THD	Percentage of Disturbance
1	Voltage Sag	1844.66850778542	0.808144743176508	10
2		1843.91964922542	0.791112984646558	13
3		1885.88190629996	0.818222236341638	16

4		1764.95676837728	0.845779415110629	19
5		1767.51822322821	0.803665884810516	22
6		1738.86588738371	0.826562130016344	25
7		1851.75390744084	0.806475686890340	28
8		1643.65692948336	0.830623536070066	31
9		1746.59539645175	0.818411514843341	34
10		1711.23212644840	0.849878601299547	37
11		1592.10945066954	0.854810607338440	40
12		1543.73255721329	0.830854273848261	43
13		1542.21841725157	0.892425822641342	46
14		1536.99913110759	0.837725528909451	49
15		1588.70712336413	0.863403633047455	52
16		1551.50415497352	0.828688591877445	55
17		1576.39218867834	0.830366227948368	58
18		1417.62366303698	0.913815401239697	61
19		1547.54586231012	0.788245904551607	64
20		1448.63703760022	0.869403113395354	67
21		1432.17796992267	0.843570293576896	70
22		1410.86661471109	0.885402706964055	73
23		1393.67512435136	0.871714578286915	76
Serial Number	**Type Of Disturbance**	**Energy**	**THD**	**Percentage of Disturbance**
24	Voltage Swell	2173.64740397426	0.787938268858297	110
25		2279.61258082177	0.722966542593641	113
26		2284.24658406713	0.760774635075082	116
27		2347.62035058281	0.745234822452356	119
28		2278.84933003584	0.776214408599151	122
29		2538.73128185516	0.722926056741288	125
30		2446.14587050752	0.715127411698478	128
31		2503.83566022815	0.757809776640451	131
32		2494.41336461101	0.770407038535508	134
33		2566.32179806263	0.760011298943580	137
34		2572.59633442265	0.759099385250080	140
35		2623.43389006050	0.731566051125643	143
36		2743.88934409987	0.721369491112171	146
37		2821.35116384528	0.734448530546236	149
38		2909.08498577240	0.729507152764653	152
39		2958.22779081275	0.702094041798141	155
40		2934.53292138688	0.712350251226900	158
41		3011.92749816679	0.686337022088169	161
42		3104.30319453026	0.693938251448025	164
43		3084.67698481064	0.719712499007757	167

44		3227.66712050837	0.694032548883071	170
45		3370.60693364886	0.700450259538943	173
46		3508.77359685689	0.673971175521145	176
Serial Number	**Type Of Disturbance**	**Energy**	**THD**	**Percentage of Disturbance**
47	Voltage Sag With Harmonics	2889.93010768245	1.13917618000961	10
48		2617.66820508133	1.16318252776349	13
49		2653.86834921120	1.14038583716545	16
50		2582.06332512933	1.19295647772904	19
51		2459.39931487060	1.19271985091484	22
52		2623.33159480022	1.13959741849667	25
53		2404.26692416639	1.21459722318114	28
54		2418.16929979591	1.13913653916371	31
55		2399.16008468090	1.14631593542878	34
56		2435.09312425675	1.10812298005239	37
57		2506.55659828315	1.10300990778028	40
58		2382.46453391917	1.12105023996227	43
59		2243.00586861118	1.17284341780918	46
60		2111.55666196798	1.18085351797349	49
61		2245.17495427879	1.17320837582986	52
62		2137.08445113128	1.18290664195303	55
63		2125.25033628711	1.13848240913434	58
64		2265.59645930541	1.11594526320815	61
65		2146.34364210499	1.12439747293825	64
66		1962.92868152108	1.25109505456410	67
67		2025.81061580753	1.21410406643884	70
68		2126.19947093102	1.10506682342570	73
69		2109.68560411845	1.13787575382262	76
Serial Number	**Type Of Disturbance**	**Energy**	**THD**	**Percentage of Disturbance**
70	Voltage Swell With Harmonics	3025.91434544454	1.12853028491160	110
71		3389.14751400147	1.06816723575892	113
72		3322.18688556468	1.11046652175864	116
73		3371.42806472994	1.11896828356351	119
74		3409.32681616769	1.11964258047278	122
75		3321.49363985781	1.14299356197107	125
76		3556.04406749528	1.12104084528245	128
77		3356.87781614119	1.18422038178371	131
78		3551.86959686065	1.14103170405816	134
79		3761.04379050435	1.11146732634563	137

80		4008.40818260186	1.06787837137104	140
81		3778.19318921926	1.18433882358836	143
82		3884.66007077840	1.14014264219373	146
83		4050.40115551218	1.11562019100055	149
84		4161.46216661026	1.08297623391394	152
85		4052.21292652092	1.10990130976027	155
86		4276.87697092564	1.08655267356049	158
87		4368.32549571182	1.14215233117137	161
88		4337.76202790961	1.13570669021963	164
89		4615.51241347160	1.07735410073492	167
90		4673.80303789524	1.12814103107087	170
91		4653.58763357889	1.13710012388355	173
92		4767.97456062097	1.12109041611628	176
Serial Number	**Type Of Disturbance**	**Energy**	**THD**	**Percentage of Disturbance**
93	Interruption	1431.01619679477	0.855913767254355	8
94		1382.73456037338	0.887174285406562	7.7
95		1372.61083994040	0.912092463583464	7.4
96		1392.25395021053	0.875106038057038	7.1
97		1439.58908536006	0.884118130677632	6.8
98		1301.32193372220	0.905437768719380	6.5
99		1543.09393057360	0.809453943127850	6.2
100		1323.86439354752	0.913392171662656	5.9
101		1444.78387497823	0.902546397040188	5.6
102		1343.45638188043	0.898550911724480	5.3
103		1357.55893534302	0.928962913999632	5.0
104		1377.20187946265	0.899060551872168	4.7
105		1337.49680257207	0.918179439411758	4.4
106		1418.08063654238	0.872269411869473	4.1
107		1358.65443973212	0.912369641812894	3.8
108		1395.23225598068	0.834490402503998	3.5
109		1362.21054288506	0.910235502389475	3.2
110		1437.66018915256	0.866270116012695	2.9
111		1373.95889705872	0.894672187495295	2.6
112		1332.67824311781	0.892170104907969	2.3
113		1373.70733129085	0.924009544389305	2.0
114		1316.63206299618	0.874442220909218	1.7
115		1349.11960963788	0.951518975627186	1.4

5.4 Results and Discussion

For BPA with settled values of learning rate η and momentum factor α, the optimum qualities are gotten by recreation with various estimations of η and α. It might be noticed that the scope of estimations of η and α ought to be somewhere around 0 and 1. At long last, an optimal combination appears to yield with an estimation of $\eta = 0.99$ and $\alpha = 0.64$. The number of iterations was 665.

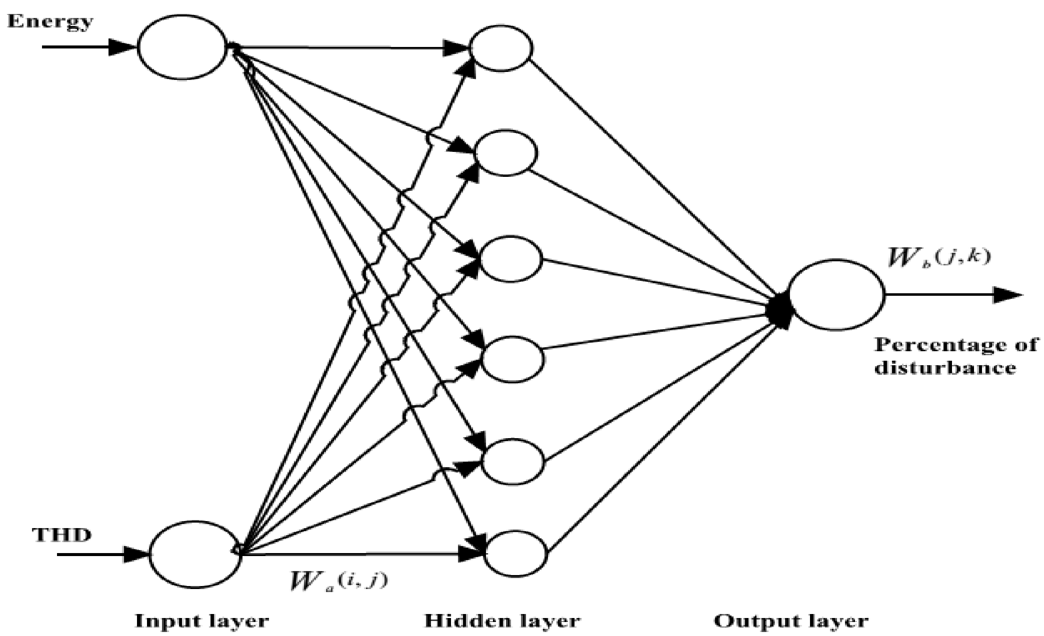

Figure 5.3 Proposed MFNN Model

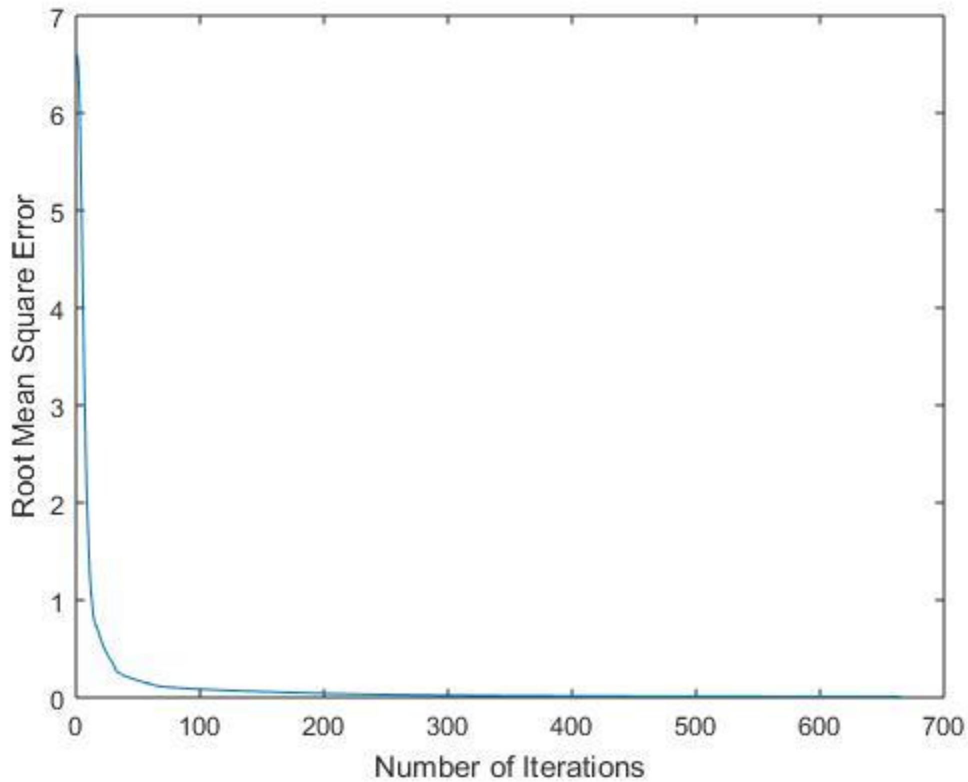

Figure 5.4 Root mean square error of the training data as a function of Number of iterations

Lastly, the percentage of disturbance for the test data are computed by using the updated weights of the network and by passing the input data in the forward path of the network. Table 5.2 shows a comparison of the exact and the estimated value of the percentage of disturbance.

Table 5.2 Comparison of the exact and estimated value of percentage of disturbance

Type Of Disturbance	Energy	THD	Percentage of Disturbance	Percentage of Disturbance (modeled)	Mean Absolute Error (%)
Sag	1764.95676837728	0.845779415110629	19	19.0000	2.1106
	1536.99913110759	0.837725528909451	49	49.0000	
	1417.62366303698	0.913815401239697	61	61.0000	
Swell	2446.14587050752	0.715127411698478	128	128.0000	
	2958.22779081275	0.702094041798141	155	155.0000	
	3370.60693364886	0.700450259538943	173	172.9527	
Sag With Harmonics	2653.86834921120	1.14038583716545	16	16.0000	
	2506.55659828315	1.10300990778028	40	40.0000	
	2126.19947093102	1.10506682342570	73	73.0000	
Swell With Harmonics	3556.04406749528	1.12104084528245	128	128.0000	
	4653.58763357889	1.13710012388355	173	172.9649	
	4767.97456062097	1.12109041611628	176	175.8057	
Interruption	1301.32193372220	0.905437768719380	6.5	6.4999	
	1373.95889705872	0.894672187495295	2.6	2.6098	
	1349.11960963788	0.951518975627186	1.4	1.4300	

Chapter 6

Classification Using Fuzzy Expert System

6.1 Introduction

The Fuzzy logic (FL) alludes to a logic framework which speaks to information and reasons in a loose or fuzzy way to reason under vulnerability. Not at all like the traditional logic frameworks, it aims at displaying the uncertain methods of thinking that assume a fundamental part in human capacity to gather a rough response to an inquiry in view of a store of information that is vague, fragmented or not absolutely solid. It is generally fitting to utilize fuzzy logic when a numerical model does not exist or exists but rather is excessively troublesome, making it impossible to encode and excessively intricate, making it impossible to be assessed sufficiently fast for constant operation. The precision of fuzzy logic frameworks depends on the information of human specialists thus, it is just as good as the legitimacy of its rules.

6.2 Fuzzy Logic Systems

A FL framework depicts the control activity of a procedure in terms of basic If-Then principles. It portrays the calculation for procedure control as a fuzzy connection between data on the procedure conditions to be controlled and the control activity. Subsequently it gives a linguistic or fuzzy model that is produced in view of human experience and aptitude as opposed to a scientific model. In a FL framework, the control activity is resolved from the assessment of an arrangement of basic linguistic principles. The advancement of guidelines requires a careful comprehension of the procedure to be controlled, however it doesn't require scientific model of the framework. The model can be multi-input multi-output or single input single output.

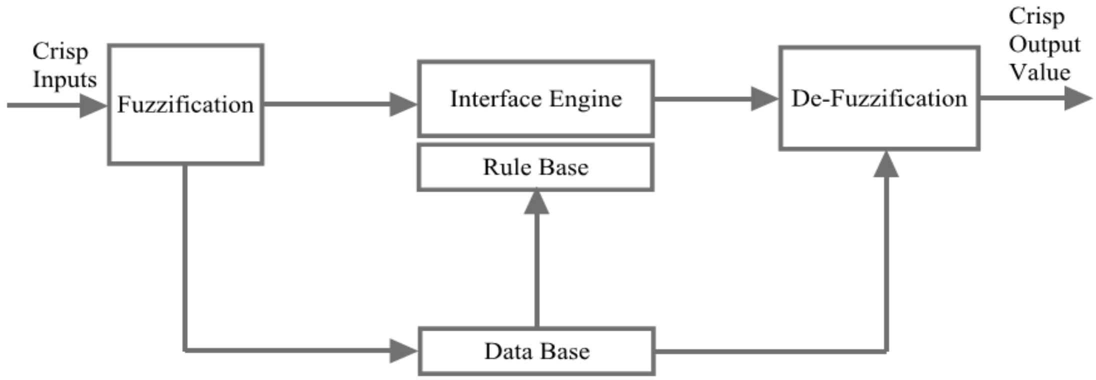

Figure 6.1 Internal structure of Fuzzy logic system

The primary segments of the FL framework are:

1. Fuzzification: The FL utilizes the linguistic variables rather than numerical variables. In this present reality, measured amounts are genuine numbers (crisp).The procedure of changing over a numerical variable into a linguistic variable is called fuzzification. It is classification of input information into reasonable linguistic values or sets.
2. Principle Base or Decision Making: This is construing fuzzy control activity from the learning of the control rules and the linguistic variable definition. It has 3 different subcomponents.
   - IF(predecessor or antecedent) part of the principle – utilization of fuzzy administrators in it.
   - THEN part of the principle – suggestion from predecessor part to the resulting part.
   - Aggregation (gathering) of the resulting of all principles. The output of every guideline is accumulated to get the last output. Some generally utilized collection strategies are Mamdani type implication (Min-Max implication), implication, Sugeno type implication and Lusing Larson type. The Mamdani type implication is utilized with the end goal of classification.
3. Defuzzification: This is the change of the derived fuzzy control activity to a fresh or non-fuzzy control activity. The decision of defuzzification methodology is a trade-off amongst exactness and computational power. A portion of the normally utilized techniques are Center of Area strategy, Height strategy, Center of gravity of biggest territory strategy and Mean of Maxima technique.

6.3 Implementation of Fuzzy Expert System for Classification Purpose

In this fuzzy expert framework, the derived elements THD and Energy of different PQ aggravations are utilized as the input to the fuzzy expert framework for classification reason. The output of the framework will not just classify the sort of disturbance. Additionally, it shows whether the aggravation is unadulterated or contains harmonics.

6.3.1 Membership Functions

The Membership functions can have distinctive shapes, for example, triangular, trapezoidal, Gaussian, bell-shaped, and so on. It can be symmetrical or uneven. MATLAB encourages the utilization of various membership functions with the assistance of certain syntax. The triangular membership function is the least difficult and most ordinarily utilized. It can be portrayed by three points shaping a triangle. In this work the triangular membership function is utilized. The fuzzy arrangement framework actualized here has two input variables and two output variables. Input variables are Energy and THD while the suggestions are "Type of disturbance" and " Pure or harmonics " which are the two output variables. Input variable Energy has five membership functions relating to the energy level of various disturbances and the information variable THD has five membership functions. Output1 which shows the kind of disturbance has three membership function and output2 which demonstrates whether the disturbance is unadulterated or contains harmonics has two membership functions.

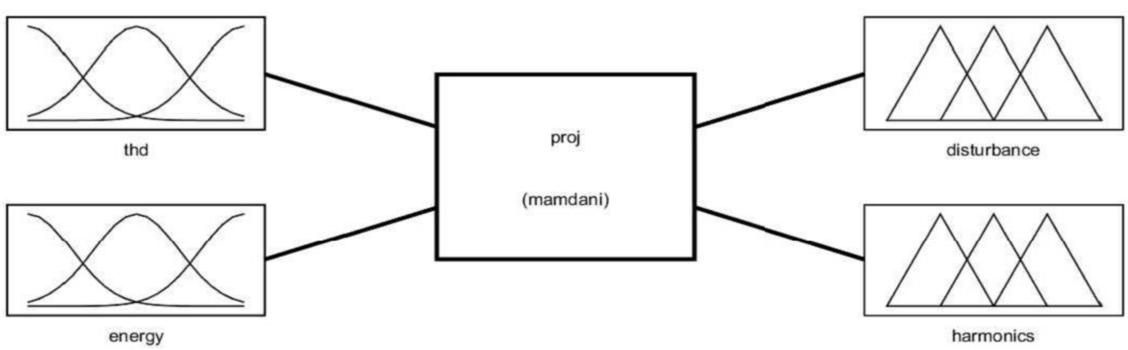

Figure 6.2 Fuzzy Inference System

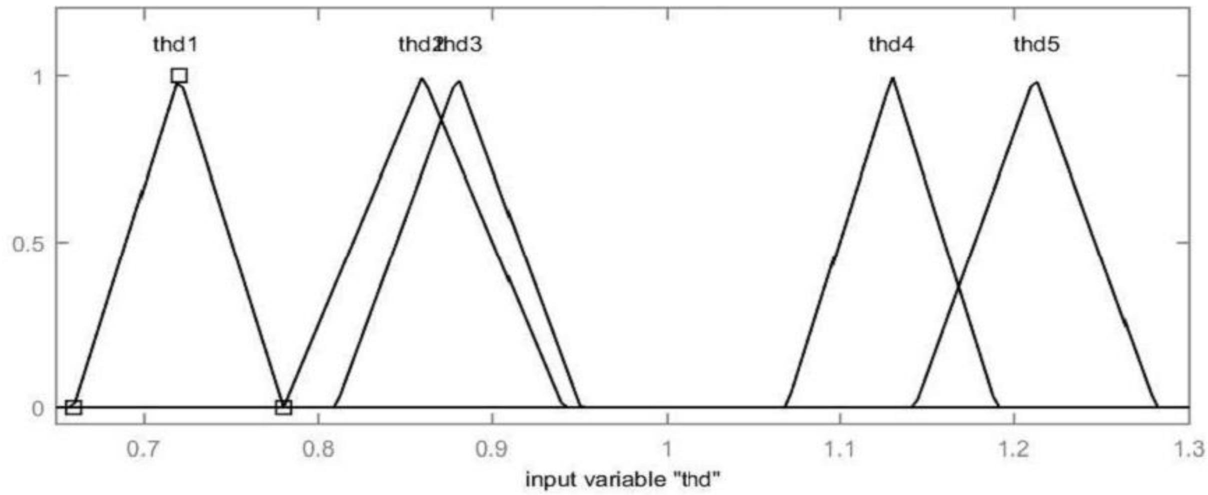

Figure 6.3 Input Membership Function for THD

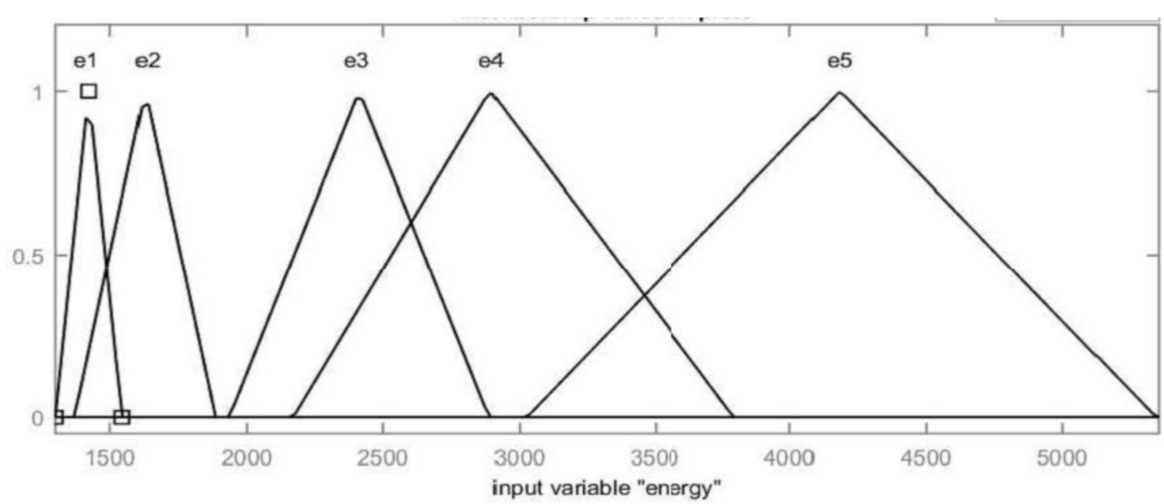

Figure 6.4 Input Membership Function for Energy

The input1 (Energy) has five membership functions which in terms of linguistic variables represented as E1, E2, E3, E4 and E5. The input2 (THD) has five membership functions named as thd1 , thd2, thd3, thd4 and thd5.

Table 6.1 Relationship between linguistic and actual values for input membership functions

Type of Disturbance	Energy	Membership Function	THD	Membership Function
Sag	1371.663 to 1885.881	E2	0.788 to 0.934	Thd2
Swell	2173.647 to 3794.441	E4	0.668 to 0.787	Thd1
Interruption	1301.321 to 1543.093	E1	0.809 to 0.951	Thd3
Sag With Harmonics	1938.218 to 2889.930	E3	1.051 to 1.251	Thd4
Swell With Harmonics	3025.914 to 5340.757	E5	1.067 to 1.184	Thd5

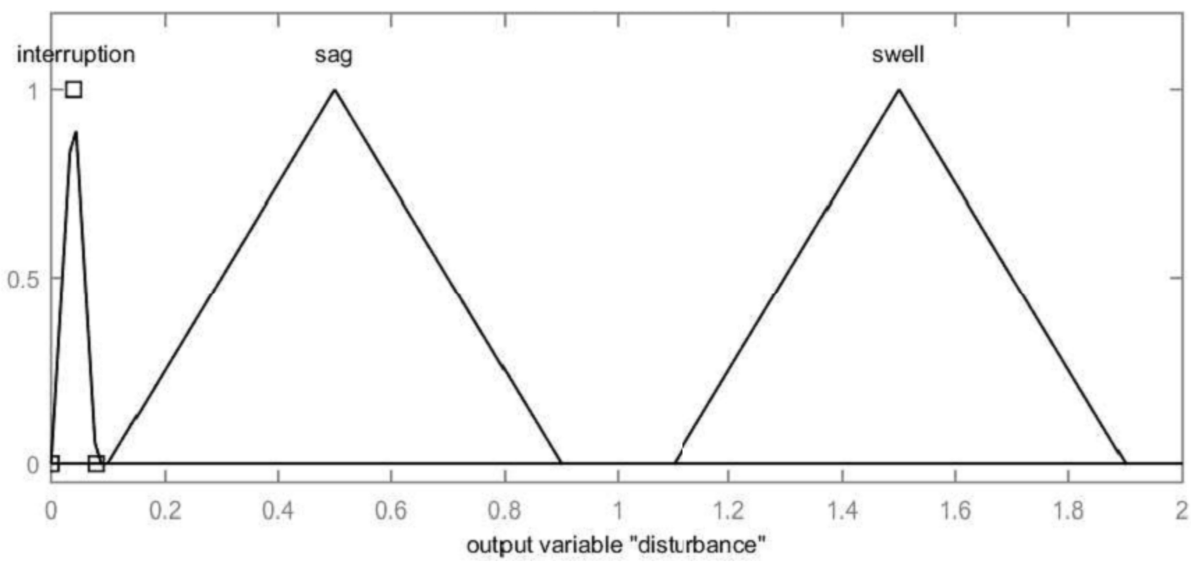

Figure 6.5 Output Membership Function for Disturbance

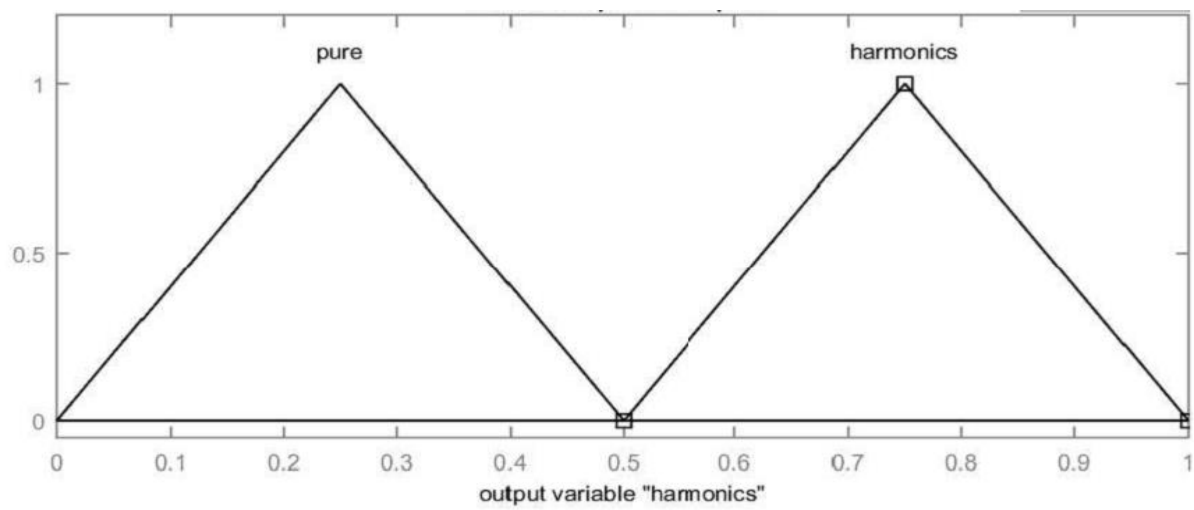

Figure 6.6 Output Membership Function for Harmonics

Table 6.2 Relationship between the linguistic and actual values of output membership function 1

Membership functions for Disturbance	Percentage of Disturbance
Sag	0.1-0.9
Swell	1.1-1.9
Interruption	0.01-0.09

Table 6.3 Relationship between the linguistic and actual values for output membership function 2

Membership functions for Harmonics	Values
Pure	0-0.5
Harmonics	0.5-1.0

6.3.2 Rule Base

From the above database, following rules are inferred for the purpose of classification:

Rule1: If Energy is E2 and THD is thd2, then disturbance is Sag.

Rule2: If Energy is E4 and THD is thd1, then disturbance is Swell.

Rule3: If Energy is E1 and THD is thd3, then disturbance is Interruption.

Rule4: If Energy is E3 and THD is thd4, then disturbance is Sag with Harmonics.

Rule5: If Energy is E5 and THD is thd5, then disturbance is Swell with Harmonics.

6.4 Classification Accuracy

Upwards of hundred specimens of disturbances in every class of power quality with different magnitude has been simulated and tested with the above fuzzy expert framework. The general exactness acquired is 94.2%. It indicates incorrectness in boundary estimations of various disturbance band else it gives extremely exact results in classifying diverse disturbances. This framework likewise shows whether the disturbance contains harmonics or not.

Table 6.4 Classification Accuracy

Type of Disturbance	Number of Samples Considered	Number of Samples Correctly Detected
Sag	100	96
Swell	100	97
Sag with Harmonics	100	94
Swell with Harmonics	100	91
Interruption	100	93

Chapter 7

Conclusion and Future Scope of the Work

7.1 Conclusion

The Detection and classification of PQ disturbances is a vital issue in the power quality examination as before any fault clearing activity, the sort of disturbance and the purpose of disturbance are expected to influence the remedial measure. In this work six distinctive PQ disturbances are viewed that also incorporates complex disturbances like sag with harmonics and swell with harmonics for the portrayal purpose. As a matter of first importance these disturbances are decomposed into different levels utilizing wavelet decomposition algorithm of wavelet transform and the type of disturbance alongside the point of disturbance was identified. This demonstrates that the wavelet transform as a signal handling device is very effective in examining the PQ disturbances that might be stationary or non-stationary in nature. The WT is a frequency space approach where the signals are examined at various frequency determination levels. The Issue is experienced in identification when the signal contains a high density of noise or low signal to noise ratio. Additionally the component vector to be separated for the arrangement reason will contain high rate of noise which may corrupt the classification exactness. Thus need emerges to de-noise the PQ disturbances before further handling. A wavelet based de-noising system executing programmed thresholding standard and soft thresholding capacity has been proposed. The PQ disturbances are de-noised. At that point the element vector is extracted. The two unique components like THD and Energy are considered for extracting the elements. An information database in light of the above two elements for distinctive PQ disturbances with different magnitude of disturbance is readied. A PQD recognition framework in view of the MFNN is demonstrated. The elements extricated are utilized as the training examples and rate of disturbance is discovered and in light of this rate of disturbance, the class of disturbance can be effortlessly discovered. The root mean square error and the mean absolute error are acquired in the training and the testing procedure individually. These are observed to be within safe limits. At that point a fuzzy expert framework taking into account Mamdani Fuzzy interface is intended for the arrangement of various PQ disturbances. Upwards of hundred number of PQ occasions with fluctuating magnitude of fault is produced in each of the PQ disturbance. They are tested with the fuzzy expert framework to acquire the grouping precision. The general grouping exactness got with Mamdani Fuzzy logic is 94.2% though if there should arise an occurrence of MFNN, mean absolute error acquired is 2.1106% which demonstrates the manufactured neural system based framework is more productive. In any case, MFNN is little slower and takes more time for training if the no of information are more as it is an iterative system. The Fuzzy interface framework confronts trouble in arranging the extreme values in each disturbance extend accurately.

7.2 Future scope of work

1. Features other than THD and energy like entropy, standard deviation etc. can be used. We can also use more than two features as the input to the PQD system using MFNN and the fuzzy expert framework.

2. Different shape of fuzzy membership function can be used other than triangular like trapezoidal, Gaussian, bell shaped etc. and further analysis can be carried out.

3. More advanced techniques of noise removal can be used to clear the noise even more efficiently.

References

[1] Quinquis, “Digital Signal Processing using Matlab,” ISTE WILEY, pp.279-305, 2008.

[2] P.S.Wright,”Short time Fourier transform and wigner-ville distributions applied to the calibration of power frequency harmonic analyzers,” *IEEE Trans.instrum.meas.* (1999) 475- 478.

[3] Y.Gu,M.Bollen, “Time Frequency and Time Scale Domain Analysis of Voltage Disturbances,” *IEEE Transactions on Power Delivery*, Vol 15, No 4, October 2000, pp 1279- 1284.

[4] G.T.Heydt, P.S. Fjeld, C.C.Liu, D.Pierce, L.Tu, G.Hensley,”Applications of the Windowed FFT to Electric Power Quality Assessment,” *IEEE Trans.Power Deliv*.Vol.14 (4) (1999) 1411-1416.

[5] R. Polikar, The Engineer’s Ultimate Guide to Wavelet analysis, The Wavelet Tutorial.March 1999.

[6] S.Santoso, W.M.Grady,E.J.Powers,J.Lamoree and S.C.Bhatt,”characterization of distribution power quality events with fourier and wavelet transforms,” *IEEE Trans.power delivery,*Vol.15,pp 247-254,jan.2000.

[7] Abdelazeem A.Abdelsalam, Azza A.Eldesouky,Abdelhay A.Sallam,”characterization of power quality disturbances using hybrid technique of linear kalman filter and fuzzy expert system,” ELSEVIER Electric power system Research 83 (2012) 41 -50.

[8] L.C.Saikia, S.M.Borah, S.Pait,”detection and classification of power quality disturbances using wavelet transform and neural network,” *IEEE annual india conference* 2010.

[9] S. Santoso, E. Powers, W. Grady, and P. Hoffmann,” Power Quality Assessment via Wavelet Transform Analysis,” *IEEE Transactions on Power Delivery*, Vol.11, No.2, pp. 924-930, April 1996.

[10] Peisheng Gao and Weilin Wu, “Power Quality DisturbancesClassification Using Wavelet & Support Vector Machine,” *IEEE Proceedings of the Sixth International Conference on IntelligentSystems Design and Applications* (ISDA'06).

[11] Atish K. Ghosh and David L. Lubkeman, “The Classification of Power System Disturbance waveforms using a Neural Network Approach,” *IEEE Transactions on Power Delivery,* Vol. 10, No. 1, January 1995.

[12] J.S. Huang, M. Negnevitsky and D.T. Nguyen, “Wavelet transform based harmonic analysis,” Australasian universities power engineering Conference and IE Aust Electric Energy Conference, pp.152-156, 1999.

[13] T.K. Abdel-Galil, E. F. EL-Saadany, A.M. Youssef and M. M. A.Salama, “On-line Disturbance Recognition utilizing Vector Quantization based fast match,”.

[14] S. Tuntisak and S. Premrudeepreechacharn, “Harmonic Detection in Distribution System Using Wavelet Transform & Support Vector Machine,” *IEEE Conference on Power Tech* 2007.

[15] Surya Santoso, Edward J. Powers, and W. Mack Grady and Antony C.Parsons, “Power Quality Disturbance Waveform Recognition Using Wavelet-Based Neural Classifier—Part 1: Theoretical Foundation,” *IEEE transactions on power delivery,* Vol. 15, no. 1, January 2000.

[16] Boris Bizjak and Peter Planinsic, “Classification of PowerDisturbances using Fuzzy Logic,”

[17] Jaehak Chung, Edward J. Powers, W. Mack Grady and Siddharth C.Bhatt, “Power Disturbance classifier using a Rule-based method and wavelet packet based hidden Markov model, “ *IEEE transactions on power delivery,* Vol. 17, no. 1, January 2002.

[18] D.Tianjun, C.Guangju and Y.Lei," Frequency Domain Interpolation Wavelet Transform based Algorithm for Harmonic Analysis of Power System," ICCCAS2004 International Conference on Communications, Circuits and Systems, Vol.2, pp.742-746, 27-29 June 2004.

[19] Wei Bing Hu, Kai Cheng Li, Dang Jun Zhao, Bing Ruo Xie, "Performance Improvement of Power Quality Disturbance Classification Based on a New Denoising Technique," Proceeding of International Conference on Electrical Machines and Systems 2007, Oct. 8~11, Seoul, Korea

[20] Sudipta Nath,Priyanjali Mishra,"Wavelet based Feature Extraction for Classification of Power Quality Disturbances," ICREPQ'11 International Conference on Renewable Energies and Power Quality,13-15 April,2011.